

REVIEW

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The use of high-frequency data in cryptocurrency research: a meta-review of literature with bibliometric analysis

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Abstract

As the crypto-asset ecosystem matures, the use of high-frequency data has become increasingly common in decentralized finance literature. Using bibliometric analysis, we characterize the existing cryptocurrency literature that employs high-frequency data. We highlighted the most influential authors, articles, and journals based on 189 articles from the Scopus database from 2015 to 2022. This approach enables us to identify emerging trends and research hotspots with the aid of co-citation and cartographic analyses. It shows knowledge expansion through authors' collaboration in cryptocurrency research with co-authorship analysis. We identify four major streams of research: (i) return prediction and measurement of cryptocurrency volatility, (ii) (in) efficiency of cryptocurrencies, (iii) price dynamics and bubbles in cryptocurrencies, and (iv) the diversification, safe haven, and hedging properties of Bitcoin. We conclude that highly traded cryptocurrencies' investment features and economic outcomes are analyzed predominantly on a tick-by-tick basis. This study also provides recommendations for future studies.

Keywords: Cryptocurrencies, High-frequency data, Intra-day data, Bibliometric analysis, Network analysis, Meta-literature review

Introduction

With the advent of advanced high-frequency data analysis techniques, finance scholars have increasingly delved into the intricate dynamics of financial markets, thereby uncovering novel insights into their behavior and interconnectivity. However, accessing high-frequency data poses a significant obstacle for relatively new and immature financial assets, such as cryptocurrencies. As a result, most early studies in this field resorted to employing daily data, inadvertently missing out on the advantages of utilizing data with higher frequencies (Corbet et al. 2018a). Nevertheless, as the infrastructure supporting cryptocurrency trading matured, collecting data at higher frequencies became possible, ushering in a new wave of cryptocurrency research that leveraged these more granular data (e.g., Katsiampa et al. 2022).

Contrary to low-frequency data, high-frequency data helps identify jumps in financial assets (Christensen et al. 2014), facilitates the detection of behavioral biases, accurate

information about market microstructures, intraday changes, and patterns that cannot be easily captured but are concealed at daily frequency (see Hansen and Huang 2016). Using high-frequency (hourly) data helps search for arbitrage trades in both short- and long-term horizons (Sifat et al. 2019). Inefficiency in cryptocurrencies can also be better detected in high-frequency (intraday) data than in low-frequency (daily) data (Zargar and Kumar 2019). Moreover, low-frequency data, even daily data, cannot reflect the swiftly changing environments in crypto markets during trading. By contrast, high-frequency data that cover shorter time horizons can improve the precision of models and the understanding of market dynamics, i.e., monitoring price dynamics and formation, trading activity, microstructures, and investor behaviors in the crypto market. From COVID-19 onwards, the literature has evaluated cryptocurrencies at high frequencies from various perspectives (Katsiampat et al. 2022).

The results reported in cryptocurrency research papers, often developed in parallel, create discrepancies stemming from differences in observation periods and variations in the data frequencies used by scholars. Alexander and Dakos (2020) found that 80 of 124 papers published between January 2017 and March 2019 used questionable and/or non-traded data in their empirical analysis. To our knowledge, no previous studies have attempted to comprehensively explore cryptocurrency literature using high-frequency data, synthesize the available findings, and provide meaningful directions for future research in this domain. To fill this gap and enhance our understanding of the role of high-frequency cryptocurrency data in shaping the cryptocurrency literature, this study employs a bibliometric analysis.

The bibliometric technique is the most popular approach for analyzing growing literature, assessing the scholarly contributions of diverse stakeholders, and helping create thematic maps for scholarly applications. In addition, we performed content analysis. We attempt to answer the following questions: What are the prevailing publication trends in using high-frequency data in cryptography-related research? Which highly influential articles leverage high-frequency data in cryptographic studies? Does a surge in the number of publications by authors or journals lead to a proportional increase in the total number of citations and getting more attention? Does publishing in highly influential journals in this field contribute significantly to an increase in the number of citations of the authors' articles? What are the primary research streams encompassing past and current themes in the cryptocurrency literature using high-frequency data? What are the prospective avenues of research within this field?

This literature review aimed to comprehensively explore diverse academic articles that have utilized high-frequency data to unravel the complexities of cryptocurrency trends, market volatility, and the interrelationships among different digital currencies. By synthesizing and critically analyzing the findings of these pivotal studies, we aimed to provide a nuanced understanding of the implications of high-frequency data analysis in shaping our comprehension of the ever-evolving cryptocurrency landscape.

This study contributes to the literature in several ways. First, we conducted a performance or citation analysis based on article production growth, contributing authors, institutions, countries, and key journals. We also examine the impact of increasing publication authors, and journals on their citations and attention. Further, we assess and identify the fields relevant to crypto market research and their associated links

with other assets that dominate the use of high-frequency datasets. This topic is underexplored in the literature. Thus, this study aimed to fill this gap by classifying the body of knowledge, contributing to the rapidly growing cryptocurrency literature, and offering specific directions for further research on cryptocurrency scholars. Our study highlights the benefits of using high-frequency data in cryptocurrency research, and we believe that it will facilitate further research in these innovative areas.

Second, we conduct a meta-analysis of the literature through bibliometric and content analyses, employing qualitative and quantitative methods to synthesize research on the cryptocurrency market, particularly emphasizing the growing utilization of high-frequency datasets. Although several alternative approaches are available for categorizing existing papers based on their primary themes and methodologies, such as a systematic literature review (Corbet et al. 2019), bibliometric analysis is rapidly gaining prominence in finance. Therefore, our contribution builds upon previous studies that utilized alternative methodologies, including a systematic literature review (Ballis & Verousis 2022; Corbet et al. 2019) or survey method (Fang et al. 2022; Holub & Johnson 2018), by integrating both meta-analysis and bibliometric review approaches.

Finally, the novelty of our study lies in its distinction from recently published bibliometric analyses of cryptocurrencies. For example, several studies have exclusively conducted bibliometric analyses focusing on Bitcoin (Mereditz-Solà & Bariviera 2019; Ramona et al. 2019; Shen et al. 2020), while others have explored cryptocurrencies from various perspectives, including their growth (García-Corral et al. 2022), economic implications (Yue et al. 2021), financial asset role (Jalal et al. 2021), adoption trends (Sousa et al. 2022), and the evolution from a technological to an economic standpoint (Jiang et al. 2021). However, our current systematic literature review and bibliometric analysis emphasize the use of high-frequency data in cryptocurrency market research. To our knowledge, no bibliometric reviews have focused on this subject.

We find that the highest number of publications is by *Ahmet Sensoy* (author) in *Finance Research Letters* (journals). Frequently publishing authors and journals are also influential, but the level of attention is not attached to the frequency of publications. Articles published in influential journals (with many citations per paper) attract more citations. The use of high-frequency data in cryptocurrency research can be divided into four major streams. The first group focuses on return prediction and the measurement of cryptocurrency volatility, which is expected given the lack of established pricing models and the high volatility in cryptocurrency markets. The second focuses on the (in)efficiency of cryptocurrencies. Market efficiency is an inherent feature of the market's microstructure. The third examines price dynamics and bubbles in cryptocurrencies, and the fourth examines the hedging, diversification, and safe haven properties of Bitcoin.

The remainder of this paper is organized as follows: Sect. "Literature background" discusses the background literature, Sect. "Data and methodology" explains the data and methodology, Sect. "Bibliometric results" describes the bibliometric results, Sect. "Avenues of future research" identifies research hotspots in the field, Sect. "Conclusions" offers future research directions, and Sect. "Conclusions" concludes the paper.

Literature background

Cryptocurrency, initially a niche product in small online communities, has evolved into a digital medium of exchange prized for its economic efficiency and rapid transaction speeds. Its journey can be traced back to the 1980s when David Chaum (1983) introduced a groundbreaking encryption method still used for web-based security. It is the foundation for modern electronic fund transfers (Bunjaku et al. 2017). In the 1990s, several digital currencies were developed; however, many of them, such as Wei Dye's money, failed to gain traction. A notable exception is PayPal, which has gradually expanded in influence. Notwithstanding past attempts to create virtual currencies, such as E-gold and Liberty Reserve in 1996 and 2006, the title of the first enduring and most famous blockchain-based cryptocurrency is Bitcoin, introduced by Nakamoto (2008). Before the inception of Bitcoin, the concept of cryptocurrency was virtually nonexistent, primarily because of concerns surrounding centralization and the legitimacy of digital currencies (Bakar et al. 2017).

The introduction of Bitcoin has ignited substantial excitement within financial markets, and this phenomenon poses an existential risk to certain conventional financial functions (Hårdle et al. 2020). Subsequently, new cryptocurrencies such as Ethereum, Ripple, and Litecoin and stable coins such as Tether have also been introduced, potentially serving as competitors or alternatives to Bitcoin. According to Statista, the cryptocurrency landscape has experienced exponential growth, expanding from 63 in 2013 to the staggering 4,501 options available today. Among these, only the top 20 account for 90% of the worldwide market share, thus achieving global dominance (Ji et al. 2019).

From a notable paper by Nakamoto (2008), who introduced Bitcoin, many papers have been published in economics, finance, computer science, management, and other fields. Cryptocurrency has become a revolutionary payment tool that serves as an alternative to traditional financial markets due to its sage of innovative technology (blockchain) and cryptography,¹ thereby ensuring a move towards the evolution of digital finance.

These newly developed digital currencies have advantages over conventional currencies, such as decentralized transactions, auditability, and anonymity, to name just a few. Still, they also contain unique risks, such as uncontrolled network operations (Johnson et al. 2014). The recent COVID-19 outbreak has spiked the interest of retail and institutional investors in the crypto market, which can be accessed from home through fintech trading sites, such as Binance and Robinhood (Long et al. 2022). This increased accessibility to digital assets has led to enhanced intraday trading in the cryptocurrency market. Moreover, improved ecosystems such as Cosmos and Polkadot facilitate crypto investors to make cross-blockchain trades that were not previously viable.

The discussion of cryptocurrencies has become a hot topic, attracting readers from industrial and academic communities (Tschorsch and Scheuermann 2016). Initially, researchers focused on understanding blockchain technology (Zheng et al. 2018; Zyskind and Nathan 2015) and the potential of Bitcoin as a substitute for traditional currencies in economics (Böhme et al. 2015; Yermack 2015). The current literature analyzing

¹ Cryptography word originated from military and different intelligence agencies those employ various codes to protect the leakage of information, for further details along with advantages and disadvantages of cryptocurrencies see, Bunjaku et al. (2017).

the financial features of the crypto market shows enormous growth from the perspective of economics and finance (see Chu et al. 2021; Kayal and Rohilla 2021; Shi and Shi 2021) because this market, with billions of dollars of capitalization, serves as a complementary currency with diversification features resembling an investible asset class (Bouri et al. 2017a; Carrick 2016; Gandal et al. 2018). Moreover, with the maturity of the blockchain space, thousands of cryptocurrencies are traded worldwide (Corbet et al. 2019). However, these digital assets demonstrate some standard features, such as heavy tails, long memory, volatility clustering, and adverse leverage effects (Fung et al. 2022), and are speculative investment tools, which means they are prone to explosiveness or speculative bubbles (Bouri et al. 2019a; Shahzad et al. 2022; Cheah and Fry 2015) because of the potential to generate higher returns for investors, thereby attracting a new group of speculators.

Despite the increased accessibility of high-frequency crypto data, most studies employ low-frequency data in the crypto market and aligned research areas. This is highlighted by a survey conducted by Bariviera and Merediz-Solà (2021), which affirms that most studies consider the daily frequency as a natural data frequency, ignoring other options. Among the most relevant studies, only a few have employed high-frequency data and considered them more efficient. Besides the findings of this survey, numerous studies have explored different aspects of cryptocurrencies, predominantly Bitcoin, by using data of daily frequency such as bubbles (Cheah & Fry 2015), hedging capabilities (Dyhrberg 2016b), liquidity, and efficiency (Wei 2018), long memory interdependency (Cheah et al. 2018), structural breaks (Thies and Molnár 2018), transaction activity (Koutmos 2018), tail risk (Borri 2019) and its dependence (Nguyen et al. 2020), long memory effects (Phillip et al. 2019), and price clustering (Urquhart 2017), volatility spillover (Yi et al. 2018), and cyber-attacks, contagion and spillover within crypto market (Caporale et al. 2021).

The crypto market offers 24 h trading throughout the year. In the existing traditional financial market, investors may hold assets for a short period of a few minutes (Glantz and Kissell 2013), and the crypto market is no different. Many online exchanges offer tools and services that enable cryptocurrency traders to trade for minutes or seconds, resulting in high profits (Brauneis et al. 2022; Chu et al. 2019). Moreover, compared to other financial instruments, cryptocurrencies demonstrate higher intraday volatility (movements of 3–5% are common), and a large portion of high-frequency trades are pursued through algorithmic trading bots, which signifies the use of high-frequency data in analyzing cryptocurrencies (Chan et al. 2022; Zhang et al. 2019b).

Several studies have supported the significance of using high-frequency data. For instance, Mensi et al. (2020) suggested that high-frequency data can locate or trace fitful market activities over time. In contrast, daily prices also differ in their calculations, which may create issues. Vidal-Tomás (2021) affirms that daily prices are either closing prices at the last closing hour of a day or the weighted averages of the hourly closing prices of a day (24 h), which are statistically different. The last hour's daily closing prices may fail to explain the daily behavior of cryptocurrencies owing to characteristic volatility, and these prices may change in the next minute. Meanwhile, weighted average daily prices may distort trader behavior, as they cause a reduction in the volatility of cryptocurrencies by averaging high-frequency (hourly) prices, leading to a persistent

time series. Recently, Yarovaya and Zięba (2022) confirmed that the return and volume of cryptocurrencies are not very sensitive to variations in the sampling intervals of high-frequency data (i.e., 5, 10, 20 min, 40 min, and hourly) but to variations between weekly, daily, and intraday data.

In line with the highlighted importance of high-frequency data, the recent research is more inclined to using of high-frequency data in exploring different aspects of cryptocurrencies, such as extreme connectedness between return and volume of cryptocurrencies at higher tail risk (Chan et al. 2022), long memory in return and volatility (Arouxet et al. 2022), rough volatility (Takaishi 2020) market complexity (Drożdż et al. 2020), price clustering (Li et al. 2020; Quiroga-Garcia et al. 2022) potential profitability by using a momentum strategy (Chu et al. 2020), volatility spillover among cryptocurrencies (Sensoy et al. 2021) and exchanges such as Binance, Coinbase, etc., (Alexander et al. 2022; Ji et al. 2021).

Previous attempts have been made to aggregate and review cryptocurrency literature. Ballis and Verousis (2022) study the impact of behavioral factors on cryptocurrencies, while Corbet et al. (2019) examine the breadth of cryptocurrency-related research. Fang et al. (2022) summarize existing research articles on cryptocurrency trading, covering topics such as trading platforms, signals, strategies, and risk management and highlighting related outcomes. Holub and Johnson (2018) map research on Bitcoin and other cryptocurrencies across various disciplines, including technical fields, economics, law, public policy, finance, and accounting. However, to our knowledge, no existing studies have provided a comprehensive literature survey of recent cryptocurrency research employing high-frequency data. Therefore, in this study, we aimed to fill this gap using a bibliometric analysis and meta-review approaches.

Data and methodology

This study employed the Scopus database to search for keywords and extracted relevant articles using a literature retrieval procedure. For data extraction, we can use all platforms such as Scopus, Web of Science (Clarivate Analytics), EconLit, IDEAS/REPEC, and Google Scholar; however, it would necessitate a huge data-cleaning process to combine all datasets (Corbet et al. 2019). Compared with WoS and EconLit, Scopus has had a broader coverage of journals since 1996. Although it has the same features as REPEC, it does not include working papers. Information on citations is available in Scopus, WoS, and REPEC but not in EconLit (Ruane and Tol 2007). However, relying on Scopus compared to other databases is based on its distinct features, that is broader coverage with citation information and more than 15,000 peer-reviewed subjects (Levine-Clark and Gil 2008), which is notably 30% larger than the WoS database (Comerio and Strozzi 2019), and allows for a more subtle analysis compared to Google Scholar, which provides limited bibliometric information for conducting bibliometric analysis.

The keywords are “crypto-market” or “cryptocurrenc*” or “crypto-currenc*” or “digital currenc*” or “Bitcoin” or “BTC” or “Ethereum” or “ETH” and “high-frequency” or “high frequency” or “intra-day” or “intraday” or “hour*” or “tick data” or “5?min” or “30?min.” This search generated 344 documents written in English and published between January 2015 and July 2022. However, we limited our search to articles published or in the press by excluding book chapters, conference papers, editorials, errata, data papers, and

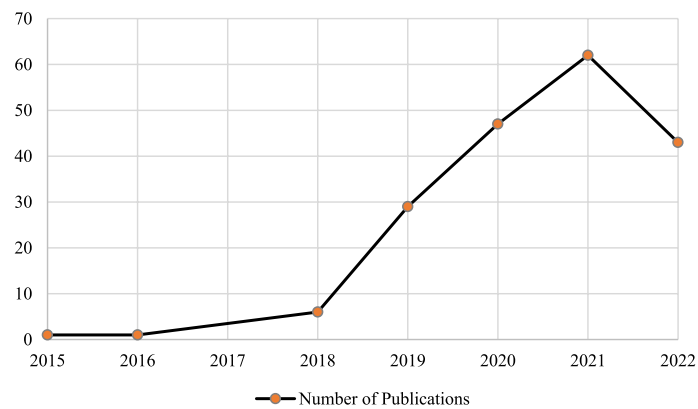


Fig. 1 Publications trend over the years

review papers, and we got 240 articles. Finally, by further scrutinizing the articles for irrelevant terms such as high-frequency band, closing hours, peak hours, work hours, intraday snapshots, etc., we obtained a final list of 189 articles as a literature sample from 2015 to 2022. This bibliometric dataset was analyzed using a bibliometric technique. The year-wise publication trends are shown in Fig. 1. A significant increase in publications using high-frequency data was observed after 2018.

Bibliometric analysis has gained popularity in several fields and has become a widely used approach in systematic reviews (Ruggeri et al. 2019; Patel et al. 2022). This approach can reveal unknown trends by collecting relevant information on a specific field or aspect of the subject. This can reduce subjective bias and steer authors to highly related fields to improve the quality of the literature review (Zupic and Čater 2015). Moreover, it helps researchers to comprehend a wider picture and creates links between publications from various sub-areas. Therefore, it is suitable for identifying the existing research state and future avenues (Paul and Bhukya 2021).

Bibliometric research methods use quantitative statistical analysis of a set of publications and then map in clusters of core authors, citations, and research institutions (De Bakker et al. 2005; Wang et al. 2021). It commonly focuses on citations, co-authors, co-citations, cartographic analyses, and bibliographic coupling (Zupic and Čater 2015). This study used bibliometric and content analyses to comprehensively examine the use of high-frequency data in cryptocurrency research to offer insight into existing research interests and discover streams of research on emerging topics in the field. Initially, the study employed a citation analysis (no networks) to highlight the volume of publications and their influential role in a specific topic. This step includes a citation analysis of authors, documents, and journals. Furthermore, regression analysis was performed to determine the authors' and journals' impact and the attention that they receive by publishing most frequently in this particular field. In addition, the authors' impact those are publishing in journals that are found influential this field. In the second stage, a co-authorship analysis was conducted to illustrate the network of collaborating authors in this field. In the third stage, cartographic or keyword co-occurrence analyses are performed to identify the evolution of research streams on a particular topic. Furthermore, co-citation (network) analysis was conducted to draw a scientific map showing the general topics or research streams through each cluster's content analysis.

Several software tools are frequently used to conduct bibliometric studies easier such as HistCite, CiteSpace, CiteSpaceV, Publish or Perish, SciMAT, BibExcel, VOSviewer, Biblioshiny, Pajek, and Gephi. Considering the diversity of the features of different bibliometric tools, we decided to use two software tools: VOSviewer (van Eck and Waltman 2014) and Biblioshiny (Aria and Cuccurullo 2017). These fit our aim of examining citation counts and classifying the literature on crypto market research utilizing high-frequency data and offering the required analysis output. These software tools were chosen because of their reliability in dealing with large datasets, comprehensive ability to sort and deal with manifold information types, flexible visual impairments, expedient settings, built-in algorithms, and provision of an eclectic range of other available network and visualization analytic tools, such as Pajek and Gephi. Moreover, these tools are superior to other potential software tools for various reasons. For example, CiteSpaceV can be an alternative. Still, it is not that flexible and requires a lot of time to master its pretty complex user interface. At the same time, Histcite is confined to WoS and unable to interpret the Scopus dataset (Fahimnia et al. 2015), Bib Excel requires extra skill set and experience to conduct a modest analysis (Ampah et al. 2021), Pajek requires “. Net” dataset.

Therefore, the software tools opted for this study are easy to use without requiring profound familiarity with clustering techniques and advanced computer skills and are freely accessible to anyone (particularly aspiring scholars) to identify existing trends and gaps in scholarly research articles and publication databases. Biblioshiny has a well-ordered and instinctive interface (Moral-Muñoz et al. 2020). We adopt it for descriptive and citation analysis, including tables and graphs, while we use VOSviewer for science mapping for multiple reasons, such as data and network visualization; readers from different disciplines can easily understand the clustering and map created by it. For identifying clusters in mapping and deriving themes from them, VOSviewer is a compelling graphic interface for users who quickly observe maps (Cobo et al. 2011). We also use Microsoft Excel for frequency analysis and analyze the citation, co-citation, and keyword co-occurrence, thereby constructing a research atlas of the propensity to use high-frequency data in cryptocurrency and exploring the research flash points and frontlines in this field.

To this end, we perform three key bibliometric techniques: co-author, co-citation, and keyword co-occurrence analyses, thereby constructing a research atlas of the propensity to use high-frequency data in cryptocurrency and exploring the research flash points and frontlines in this field. A roadmap for this study is shown in Fig. 2.

Bibliometric results

This section reports the bibliometric results: the performance analysis of authors, their affiliated institutions, nations, and publishing journals in the form of citation tables using Biblioshiny and network analysis, including co-citation, co-authorship, and keyword co-occurrence networks generated through VOSviewer.

We explain the function of VOSviewer in network analyses. It is a compelling network visualization tool for structures comprising several elements based on a distance-based vision approach. This creates networks or maps based on the data. Generated networks contain items or nodes representing objects of interest, such as

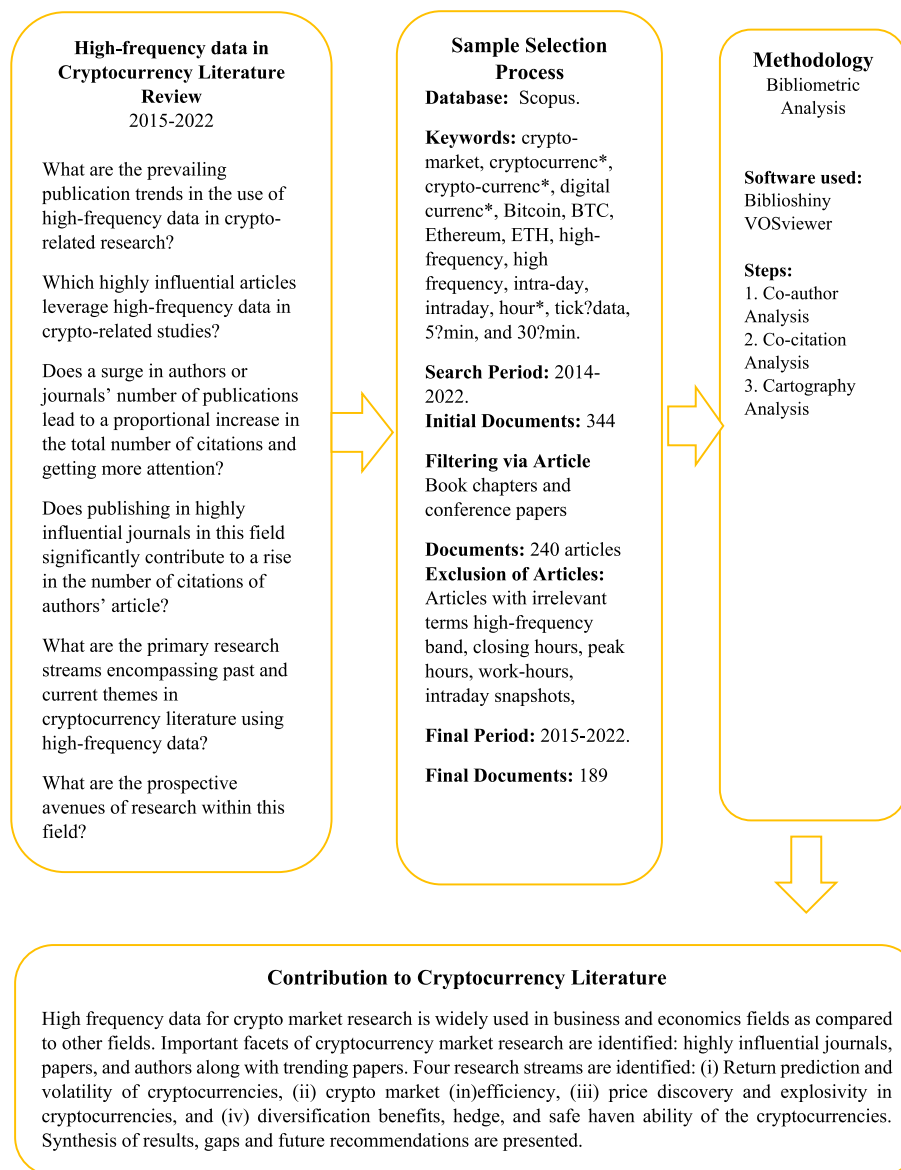


Fig. 2 Road map from data extraction to analysis

authors, sources, countries, keywords, and lines that demonstrate the connection or relationship between them (every pair of items) in the form of co-citation and co-occurrence (van Eck and Waltman 2019). The strength of the individual links was designated as a positive numerical value. This relationship becomes stronger, corresponding to higher values. The sum of the times two items (e.g., authors) are quoted together indicates a link's strength. The items were grouped into clusters where every node was ascribed to one cluster. The number of resulting clusters depends on clustering parameters, such as the smallest cluster size. This clustering analysis allowed the samples to be engraved into smaller, more homogenous groups that could be recognized and explored. However, attaining the highest homogeneity among separate clusters in our analysis was impossible. The clustering technique requires a relevant

and specific algorithm to solve an optimization query or problem (for details see, Waltman et al. 2010). In doing so, VOSviewer utilizes a smart local moving algorithm (Waltman and Van Eck 2013). Therefore, network analyses were performed using VOSviewer software.

The figures or network diagrams generated through VOSviewer use clustering procedures to allot articles with higher strengths to create results (networks) displayed in different colors. As described earlier, nodes or items represent authors, documents, keywords, etc., and their size signifies highly cited or co-cited literature. Edges represent relations in which the closeness of two nodes indicates a higher strength of the items (e.g., authors) and the co-citations or relations between them. However, they are distinguished from each other based on the variation in their total strength links, weighed-degree (computation is a built-in feature of VOSviewer), or other centrality measures such as degree, betweenness, and closeness centralities (can be computed through Gephi and Pajek). Therefore, the network relationship between the item (authors, documents, etc.) clusters helps determine the strength of the connection among the clusters that create a whole cluster analysis diagram of a discipline, field, or specific topic (Li et al. 2017).

Performance analysis

This section presents a performance analysis of the authors, their affiliated institutions, countries, and journals. We also categorize the top-trending and most influential articles published in this field. Furthermore, we examined the impact of the number of authors' and journals' publications on their citations, attention, and publishing in influential journals.

Citation analysis

Citation analysis is a widely used method for assessing the impact of a publication (Ding and Cronin 2011) through the citation numbers that an article receives from other authors (Zupic and Čater 2015). From the 189 sample documents, 86 sources, and 395 authors, we report the top 11 authors, journals, and countries, their respective numbers of articles produced (Table 1), and their influence or higher number of citations (Table 2) on the subject. We also categorized the highly cited papers (Table 3) and top-trending papers (Table 4).

Table 1 shows the classification of authors, journals, and affiliated countries at the forefront of publishing high-frequency cryptocurrency market research. For instance, *Ahmet Sensoy* was the most prolific author in this area, with the most publications. *Finance Research Letters* is the most frequent publisher of high-frequency cryptocurrency market research, with the *United Kingdom* being the top-affiliated country.

Table 2 presents the categorization of authors, journals, and countries of affiliation associated with highly cited articles on high-frequency cryptocurrency market research. For instance, *Ahmet Sensoy* is this field's most frequently cited author. *Finance Research Letters* is the most influential journal on this topic, with the *United Kingdom* being the primary country of affiliation. From this list of papers, we can infer considerable research on cryptocurrency pricing and trading, focusing on Bitcoin. Researchers are exploring topics such as price discovery, volatility forecasting,

Table 1 Highly publishing authors, journals, and affiliated countries

Authors	TPA	Sources	TPS	AC	TPC
Ahmet Sensoy	8	Finance Research Letters	26	UK	30
Shaen Corbet	7	Physica A: Statistical Mechanics and Its Applications	13	US	27
Elie Bouri	7	Research In International Business and Finance	10	Germany	21
Paraskevi Katsiampa	5	International Review of Financial Analysis	9	China	20
Konstantinos Gkillas	5	European Journal of Finance	8	Canada	14
Andrew Urquhart	4	North American Journal of Economics and Finance	6	Turkey	13
Dirk Baur	4	Journal of International Financial Markets, Institutions and Money	5	Australia	11
Walid Mensi	4	Financial Innovation	4	Ireland	10
Stephen Chan	4	Applied Economics	4	Spain	10
Jeffrey Chu	4	Applied Economic Letters	4	Japan	10
Yuanyuan Zhang	4	Economic Letters	3	Greece	9

TPA Total publications of an author is a measure of the academic output of a researcher. *TPS* Total number of publications of a source or journal. *AC* Affiliated countries or a country from which the publishing author is affiliated. *TPC* Total number of publications of authors affiliated with a country that is used as a metric to gauge the research and academic output of that country

Table 2 Highly influential authors, journals, and countries

Authors	TCA	Sources	TCS	AC	TCC
Ahmet Sensoy	297	Finance Research Letters	579	UK	615
Peter Molnar	249	Physica A: Statistical Mechanics and its Applications	398	Australia	412
Shaen Corbet	223	Journal of International Financial Markets, Institutions and Money	289	Turkey	322
Andrew Urquhart	193	International Review of Financial Analysis	265	Ireland	267
Paraskevi Katsiampa	135	Research in International Business and Finance	151	China	230
Dirk Baur	123	Economic Letters	103	Brazil	221
Walid Mensi	90	Chaos	99	US	197
Thomas Dimpfl	80	Journal of Futures Market	54	Germany	183
Stephen Chan	76	North American Journal of Economics and Finance	49	Spain	159
Jeffrey Chu	76	Financial Innovation	30	Viet Nam	157
Yuanyuan Zhang	76	European Journal of Finance	23	Canada	121

TCA Total citation of an author is a measure of the impact of a researcher. *TCS* Total number of citations of a source or journal. *AC* Affiliated countries or a country from which the publishing author is affiliated. *TCC* Total number of citations of authors affiliated with a country that is used as a metric to gauge the research impact of that country

price dynamics, correlations, inefficiencies, liquidity, transaction costs, and technical trading. This shows that the cryptocurrency market is gaining significant attention from researchers and investors and that high-frequency data and trading techniques are used to gain insight.

Table 3 presents the classification of highly cited or impactful papers that use high-frequency data and cover various topics. For instance, Brandvold et al. (2015) explored price discovery on Bitcoin exchanges, which has had a major influence on cryptocurrency research using high-frequency data. Urquhart and Zhang (2019) examined the hedge and safe haven abilities of Bitcoin for currencies using intraday data, which is the second most influential paper on cryptocurrency research that relies on high-frequency data.

This list covers the top ten papers that are cited the most on the subject.

Table 3 Highly influential papers

References	Title	Source	TC
Brandvold et al. (2015)	Price discovery on Bitcoin exchanges	Journal of International Financial Markets, Institutions and Money	158
Urquhart & Zhang (2019)	Is Bitcoin a hedge or safe haven for currencies? An intraday analysis	International Review of Financial Analysis	144
Peng et al. (2018)	The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression	Expert Systems with Applications	117
Chen et al. (2020)	Fear Sentiment, Uncertainty, and Bitcoin Price Dynamics: The Case of COVID-19	Emerging Markets Finance and Trade	108
Alvarez-Ramirez et al. (2018)	Long-range correlations and asymmetry in the Bitcoin market	Physica A: Statistical Mechanics and its Applications	108
Sensoy (2019)	The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies	Finance Research Letters	103
Aalborg et al. (2019)	What can explain the price, volatility and trading volume of Bitcoin?	Finance Research Letters	91
Katsiampa et al. (2019)	High frequency volatility co-movements in cryptocurrency markets	Journal of International Financial Markets, Institutions and Money	90
Dyhrberg et al. (2018)	How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets	Economics Letters	73
Nakano et al. (2018)	Bitcoin technical trading with artificial neural network	Physica A: Statistical Mechanics and its Applications	59

This list covers the top ten papers that are cited the most on the subject.

Table 4 Top trending papers

Author	Source	Citations/year
Urquhart and Zhang (2019)	International Review of Financial Analysis	36.0
Chen et al. (2020)	Emerging Markets Finance and Trade	36.0
Sensoy (2019)	Finance Research Letters	25.8
Peng et al. (2018)	Expert Systems with Applications	23.4
Aalborg et al. (2019)	Finance Research Letters	22.8
Katsiampa et al. (2019)	Journal of International Financial Markets, Institutions and Money	22.5
Alvarez-Ramirez et al. (2018)	Physica A: Statistical Mechanics and its Applications	21.6
Brandvold et al. (2015)	Journal of International Financial Markets, Institutions and Money	19.8
Chen et al. (2020)	Journal of Computational and Applied Mathematics	18.3
Baur and Hoang (2021)	Finance Research Letters	18.0
Naeem et al. (2021)	Physica A: Statistical Mechanics and its Applications	16.0

Table 4 classifies the top articles that employ high-frequency data and encompass a variety of topics based on their higher citations per year. Urquhart and Zhang (2019) are the most trending papers in cryptocurrency research that explore the investment characteristics of Bitcoin as a hedge and safe haven. Chen et al. (2020) study examining the impact of fear and uncertainty on Bitcoin price dynamics during COVID-19 is the second most widely referenced study. In explaining the impact of articles, it is interesting to note that some articles reported in Table 3, for example, Dyhrberg et al. (2018) and Nakano et al. (2018), are not reported in Table 4 because they have fewer citations per

Table 5 Regressions for authors’ publication impact

Panel A: Publications’ impact on author’s citations					
Dependent variable: TCA			Dependent variable: C/A		
Variable	Citations		Variable	Attention	
	Estimated Coefficient	p value		Estimated Coefficient	p value
Constant	73.812	0.000	Constant	98.948	0.000
NP	12.131	0.002	NP	− 14.769	0.000
Panel B: Publications’ impact on journal’s citations					
Dependent variable: TCJ			Dependent variable: C/J		
Variable	Citations		Variable	Attention	
	Estimated Coefficient	p value		Estimated Coefficient	p value
Constant	− 12.930	0.084	Constant	12.686	0.000
NP	22.455	0.000	NP	0.569	0.376
Panel C: Impact of influential Journal’s publications on author’s citations					
Dependent variable: TCA			Citations		
Variable			Estimated coefficient	p value	
Constant			71.716	0.000	
TCJ			0.057	0.000	

NP Number of articles published, TCA Total citations of authors, TCJ Total citations of journals, C/A Citations per article, and C/J Citations per journal Functions of Panel A are $TCA = f(TPA)$, and $C/A = f(TPA)$, for panel B, $TCJ = f(TPJ)$, and $C/J = f(TPJ)$. While function of panel C is $TCA = f(TCJ * \text{No. of articles published in journal})$

year. Whereas two articles reported in Table 4, Baur and Hoang (2021) and Naeem et al. (2021), are not reported in Table 3 because they are not highly cited, but their per-year citations are higher.

Regression analysis

We use the dataset consisting of authors and journals’ number of publications, the total citations they received for articles, and citations per article to run OLS regressions in which we examine the link between authors and journal publication count to their corresponding citations and attention, as well as influential journals’ role in getting more citations (see Table 5).

Table 5 presents the regression results for the three panels. In panel A, we show that an author’s increase in the number of articles significantly increases the number of citations while reducing the citations per article. This implies that publishing may improve the author’s total citation count, but at the same time, it can adversely affect the average number of citations per article. The reduction in average citations per article may result from multiple factors, such as publishing in diverse research areas and variation in the importance of topics. For example, groundbreaking articles may get higher citations and reworking, or articles not aligned with the prevailing research trends cannot receive the same level of attention. This result was generated using the total number of authors’ citations (right panel A of Table 5) and citations per article (left panel A of Table 5) as dependent variables and the number of publications as a regressor. Similarly, in panel B,

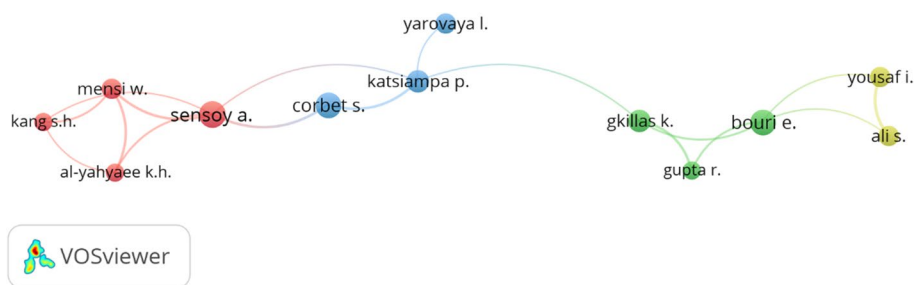


Fig. 3 Co-author network of authors researching cryptocurrencies

we repeat the same regressions with the journals’ number of articles as the independent variable and the journals’ total citations (right panel B of Table 5) and average citations per journal (left panel B of Table 5) as the dependent variables. We find that an increase in the journals’ number of publications enhances their citations; however, the attention and average citations per journal results are insignificant. Finally, in Panel C, we investigate the impact of publishing in highly influential journals (here, we consider highly cited journals publishing in this field) by running a regression for authors’ total citations (independent variable) and journals’ total citations. The results demonstrate that publishing in journals whose articles are most frequently cited because of publishing on similar topics, fields, or impactful content may increase authors’ citations.

Network analysis

Co-authorship analysis

Co-authorship analysis enables us to create links between authors, institutions, and countries researching a subject or topic (Van Eck and Waltman 2014). In our analysis of co-author networks using high-frequency data in crypto markets, we maintain our criteria at a minimum of five documents per author, which generates a network of 14 authors distributed into four clusters (see Fig. 3). The colors of the clusters varied, with Cluster 1 in red, Cluster 2 in green, Cluster 3 in blue, and Cluster 4 in yellow.

Keywords co-occurrence analysis

Keywords: words used in a paper to reflect content. The authors mostly index keywords based on the influence of their predecessors and the connections between keywords in the article. When sufficient authors use similar keywords and accept those connections in their articles, they can be used to explore topics or hotspots in a field (Whittaker 1989). Co-word analysis reveals patterns or trends in any discipline by measuring the strength of linkages between keywords. In contrast, the co-word network, based on the frequency of their co-occurrences, reflects content similarities or words with similar meanings (Ding et al. 2001). We created a keyword co-occurrence network by selecting the authors’ keywords with a minimum of five occurrences to identify the evolution of research flashpoints and embedded relevant topics.

The keyword co-occurrence network generated five clusters (Fig. 4). The first cluster in violet focuses on assessing the volatility of cryptocurrencies, specifically Bitcoin, while the second cluster in yellow focuses on the price discovery and market

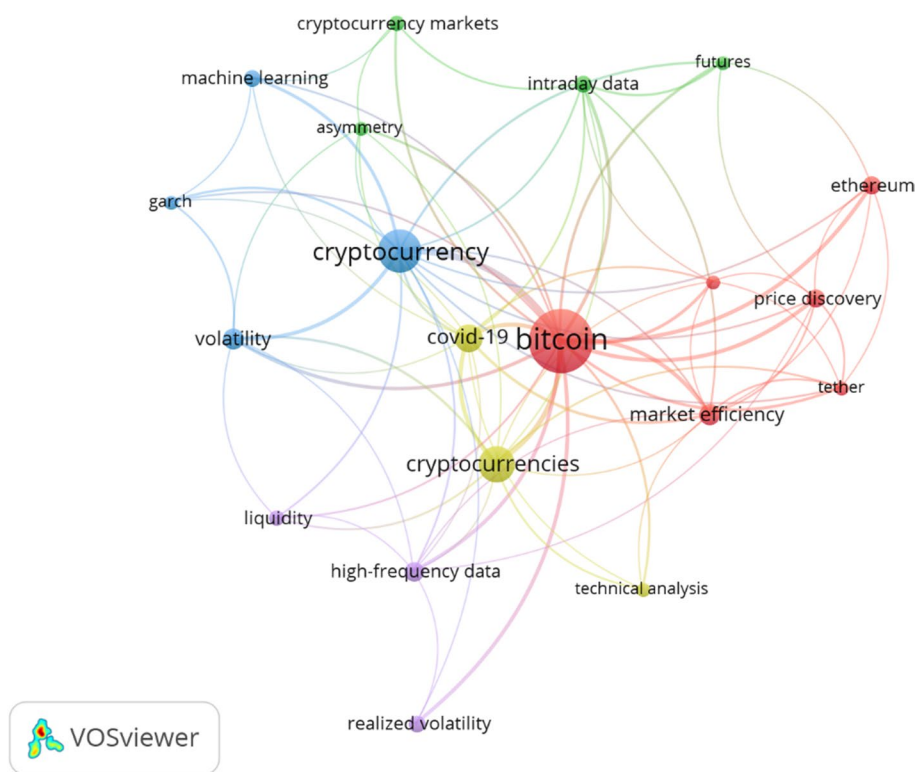


Fig. 4 Keywords co-occurrence network of cryptocurrencies

efficiency of Ethereum and the stablecoin, that is, Tether. The third cluster, in red, highlights the role of the volatility and liquidity of cryptocurrencies using high-frequency data. The fourth green cluster focuses on asymmetry in cryptocurrency futures. The fifth cluster in blue shows the safe haven ability of Bitcoin and gold during COVID-19.

Co-citation analysis

Co-citation analysis reveals the relationship between two papers if they are concurrently cited by a third (Small 1973). This shows the relationship by distributing documents with higher strength in the form of a network or clusters using clustering methods. This relationship can be used to examine the commonality, centrality, and progression of various research fields. We performed a co-citation analysis using VOSviewer and selected 20 as the minimum number of citations for an author.

This generated four clusters illustrated in different colors (see Fig. 5). Cluster 1 highlights the focus of studies on return predictions and the measurement of volatility in cryptocurrencies. Cluster 2 (green) includes studies focusing on the informational (in)efficiency of cryptocurrencies. Cluster 3 (red) represents the studies on price discovery and speculative bubbles in cryptocurrencies. Cluster 4, in blue, represents research contributing to portfolio diversification, examining the co-movement, spillover, hedge, and safe haven abilities of cryptocurrencies against other assets.

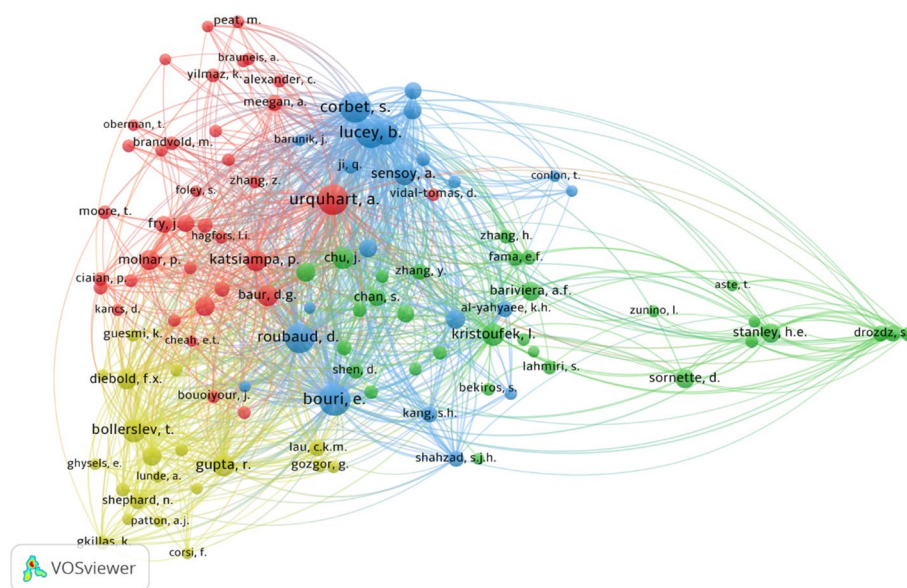


Fig. 5 Co-citation network of authors researching cryptocurrencies

Identification of major streams of cryptocurrencies research

We performed content analysis (Potter and Levine-Donnerstein 1999) to reveal, arrange, and validate the research streams identified by the bibliometric analysis. This analysis reveals the concepts, classifications, evolution, and current research streams in cryptocurrency literature. Based on this, we identify four major cryptocurrency research streams through a co-citation network of cited authors (Fig. 5). Persson (1994) noted that citing publications constitute a research front, while cited publications form an intellectual base.

Return prediction and volatility in cryptocurrencies

This stream of research focuses on the peculiarities of return prediction and volatility forecasting in cryptocurrencies, emphasizing high-frequency data and various volatility models.

Return prediction and volatility in cryptocurrencies have been studied since the introduction of Bitcoin by Nakamoto (2008). The volatile nature of cryptocurrencies is attributed to their newness compared with equity markets (Katsiampa 2017). Various factors have been found to drive Bitcoin prices, such as searching sites (Kristoufek 2013), market forces (Ciaian et al. 2016a), economic fundamentals (Li and Wang 2017), transaction speed (Corbet et al. 2018a), market attention (Urquhart 2018), trading volume (Balcilar et al. 2017; Bouri et al. 2019b), economic policy uncertainty (Demir et al. 2018; Fang et al. 2019), cryptocurrency liquidity (Wei 2018), Google search index (Bleher and Dimpfl 2019; Nasir et al. 2019), and Twitter tweets (Karalevicius et al. 2018; Shen et al. 2019). In addition to price, these factors have been found to predict cryptocurrency returns, volume, and volatility. Various models and machine learning techniques, such as long-short-term memory neural networks (Alonso-Monsalve et al. 2020; Lahmiri and Bekiros 2019; McNally et al. 2018) and support vector machines (Akyildirim et al.

2021), have been employed to predict cryptocurrency returns. Studies show that cryptocurrency liquidity relies on specific variables and is irrelevant to global financial market variables (Brauneis et al. 2021). Studies have also analyzed crypto market liquidity using high-frequency data (e.g., Dyrberg et al. 2018; among others).

After introducing realized volatility based on high-frequency data by Anderson et al. (2003), and the provision of a framework for its integration into lower frequency return distributions and volatilities (Andersen et al. 2003), it is used to study the stochastic properties of returns (Barndorff-Nielsen and Shephard 2002). In doing so, several volatility-based models, i.e., ARCH (Engle 1982) and GARCH (Bollerslev 1986), jump detection methods within realized volatility by separating bi-power variation and realized variance (Andersen et al. 2007; Barndorff-Nielsen and Shephard 2003, 2004; Huang and Tauchen 2005), and up-and downside realized measures (semi-variances) entirely based on upward and downward intraday price fluctuations (Barndorff-Nielsen et al. 2006). High-frequency data can accurately assess volatility asymmetries over longer daily return horizons (Bollerslev et al. 2006). Subsequently, methods for filtering out rare and large jumps were introduced (Tauchen and Zhou 2011). However, volatility or volatility jumps can be predicted by several factors, such as geopolitical risk (Gkillas et al. 2018). Moreover, very good and bad news have diverse impacts on volatility. For example, relatively good (intra-daily) news reduces future or next-day volatility (Chen and Ghysels 2011). The prediction of Bitcoin's realized volatility depends on historical realized volatilities and jumps (Qiu et al. 2021). For instance, Patton and Sheppard (2015) argue that future volatility highly depends on the volatility of past negative returns and that the sign of the jump matters for the impact of price jumps on volatility, such as positive (negative) jumps lower (raise) future volatility. Moreover, co-jumping behavior in the volatility of cryptocurrencies may spark future jumps (Gkillas et al. 2022).

Corsi (2009) recommends the HAR-RV model as a better method to reproduce the key empirical properties of financial returns (self-similarity, long memory, and fat tails). However, several studies (e.g., Dyrberg 2016a; Guesmi et al. 2019; Katsiampa 2017; Yu 2019; among others) examine the return prediction and volatility of cryptocurrencies using other volatility models (e.g., Bergsli et al. 2022; Chu et al. 2017; Diebold and Yilmaz 2012, 2014; Hansen et al. 2012; among others). Studies also examine volatility cascades in cryptocurrencies against the US dollar (Gradojevic and Tsiakas 2021) and volatility spillover among cryptocurrencies (e.g., Yousaf and Ali 2020).

High-frequency data are an efficient way to predict cryptocurrency returns (Vidal-Tomás 2022). Volume and frequency are inversely proportional (Yarovaya and Zięba 2022). Thus, future research topics include detecting price manipulation in cryptocurrencies at the intraday level, using feature selection techniques to improve accuracy, analyzing the impact of hard and soft forks on intraday reversal and momentum, assessing time-based momentum strategies during price crashes and sharp recovery using high-frequency data (Wen et al. 2022), and examining causal patterns between Bitcoin and other cryptocurrencies. Additionally, the volume-return relationship of cryptocurrencies (Balcilar et al. 2017; Yarovaya and Zięba 2022) can be examined with the inclusion of seasonality and volatility effects.

Similarly, using machine learning approaches such as recurrent neural networks and long short-term memory, new research can predict Bitcoin's intraday price dynamics

and identify its drivers (e.g., online sentiment and media hype). Furthermore, we provide prospective avenues for researchers in this field. For instance, Gkillas et al. (2020) suggest examining the macrofinancial determinants of crypto market jumps, and Grobys and Huynh (2022) propose assessing the impact of jumps in stablecoins. Gkillas et al. (2022) suggest assessing the impact of cryptocurrencies and the jumping behavior of other financial assets (upside, downside, and large and small jumps). Finally, volatility forecasting requires models with different data frequencies. The in-sample and out-of-sample forecasts can be reconciled at the short-, medium-, and long-term horizons.

(In)efficiency in the cryptocurrency market

Studies have identified various factors and developed different models or approaches that can predict cryptocurrency prices, challenging the efficient market hypothesis (all information is already reflected in prices). Research on cryptocurrency price prediction has led to an investigation of the efficiency of the cryptocurrency market based on the efficient market hypothesis. Increased liquidity makes cryptocurrencies inefficient and less predictable (Brauneis and Mestel 2018).

Similar to other assets, stylized facts such as fat-tailed distributions, volatility clustering, long memory features (Bariviera 2017; Bariviera et al. 2017; Chu et al. 2015; Cont 2001; Takaishi 2018; Urquhart 2017), adaptive patterns of long memory (Khuntia and Pattanayak 2020), interactions among returns, volatility, volume, and bid-ask spread (Eross et al. 2019), and asymmetric relations with price trends are observed in cryptocurrencies (Nadarajah and Chu 2017). There is also evidence of strong asymmetric reverting behavior in Bitcoin for negative returns, whereas excessive levels of persistence are revealed for positive returns (Corbet and Katsiampa 2020). In a similar vein, studies examine and analyze the microstructure properties or their impact on cryptocurrencies (e.g., Scaillet et al. 2020), stylized facts including multifractal properties (Stavroyiannis et al. 2019) by utilizing high-frequency data and different methods such as volatility autocorrelation, multi scaling effects, etc., (Drożdż et al. 2018), including Detrended Fluctuation Analysis, and Hurst exponents (Zhang et al. 2019a), and herding behavior during the COVID-19 pandemic and other different situations (e.g., Choi et al. 2022; Jalal et al. 2020; Mandaci and Cagli 2022; Yarovaya et al. 2021). Moreover, Bitcoin may respond more to negative than positive news (Fang et al. 2019). Negative market sentiment predicts bitcoin returns, volatility, trading volumes, and jumps. For instance, bitcoin returns and volatility fall in response to news relevant to crypto fraud and cyberattacks (Rognone et al. 2020). Moreover, evidence indicates that behavioral patterns in Bitcoin-related Google searches and tweets amplify herding, whereas EPU patterns and dependence between foreign exchange and equity markets dampen herding (Philippas et al. 2020). Thus, events like the COVID-19 pandemic may steer cryptocurrency markets away from weak-form efficiency, making it possible to predict future cryptocurrency prices based on past information. Furthermore, long-range dependence on cryptocurrency price returns and their amplification during the COVID-19 period points to inefficiency (Naeem et al. 2021).

In efficient markets (Fama 1970), past information should be reflected in prices; however, Bitcoin's anti-persistence behavior (Takaishi 2021) indicates a frequent reversal in its moving direction, and asymmetric volatility induces inefficiency (Kristoufek 2018;

Phillip et al. 2018), thereby increasing the possibility of achieving abnormal profits (Caporale et al. 2018). However, Bitcoin has predictive information for the price trends of other cryptocurrencies (Wang and Ngene 2020). To study the efficiency of crypto markets, several approaches, such as the Hurst exponent (Carbone et al. 2004), multifractal analysis (Drożdż et al. 2010; Jiang et al. 2018), wavelet and detrended fluctuation analysis (Oświęcimka et al. 2006), detrending analysis (Oświęcimka et al. 2014), and multifractal detrended analysis (Kantelhardt et al. 2002) have been employed for various assets (Jiang et al. 2019; Wang and Wang 2021) and or cryptocurrencies (Alvarez-Ramirez et al. 2018; Aslan and Sensoy 2020; Bariviera 2017; da Silva Filho et al. 2018; Dimitrova et al. 2019; Kristoufek 2018; Takaishi and Adachi 2020; Takaishi 2018; Urquhart 2016; Zhang et al. 2018).

Along with the approaches used to study the multifractal properties of Bitcoin, efficiency in the cryptocurrency market is examined through benchmark currency, varying sampling frequency, etc. (Bariviera 2017; Chu et al. 2019; Khuntia and Pattanayak 2018; Jiang et al. 2018; Sensoy 2019; Tiwari et al. 2018; Vidal-Tomás and Ibañez 2018). Despite the various perspectives, the primary conclusion of this study is that Bitcoin is inefficient (Kristoufek 2018; Mensi et al. 2019; Nadarajah and Chu 2017; Urquhart 2016) but may achieve weak-form efficiency over time (Chu et al. 2019; Gradojevic et al. 2022). Based on evidence of increased economic value and trading anomalies during the COVID-19 pandemic, Wen et al. (2022) suggest that traders can form a profitable strategy based on historical intra-day returns, leading to an inefficient cryptocurrency market.

However, as previous studies have examined herding behavior in bitcoin futures markets (e.g., Blasco et al. 2022), investigating stylized facts and empirical results of cryptocurrency futures and spot markets is important. Similarly, herding effects and their intensity should be studied across countries and markets while considering the impact of distinct factors. Examining the macro-financial, sentiment, psychological, and uncertainty determinants of herding behavior in the cryptocurrency market can provide detailed insights. The efficiency of cryptocurrencies in different regimes (upward and downward trends and asymmetric behavior) should be assessed, and the relative efficiency of other assets with cryptocurrencies should be compared. Variations in persistence and market efficiency should be evaluated during the outbreak of COVID-19 and the Ukraine-Russia War, and the anomalies and efficiency of more and less liquid cryptocurrencies should be assessed. Furthermore, as Dong et al. (2022) suggest, anomalous returns (displaying long or short legs) differ from those identified in equity markets, and the fundamental economic mechanisms of market anomalies can be explored in future research.

Price discovery and speculative bubbles in cryptocurrencies

In the preceding section, we discussed how the EMH and asset pricing theory follow the assumption that asset prices move around or mean revert to their fundamental value. The presence of explosiveness or bubbles in asset prices indicates a significant departure from their fundamental values. Similarly, studies have attempted to predict bitcoin prices through different approaches, such as the network-based properties of blockchain or bitcoin transaction graphs (e.g., Greaves and Au 2015). However, according to Tiwari et al. (2018) and Urquhart (2016), Bitcoin's fundamental value is

zero, and individual investors drive the market such that noise traders can distort the price discovery mechanism, leading to inefficiencies. Therefore, in addition to return and volatility forecasting, price explosiveness or bubbles in the cryptocurrency market indicate inefficiency. Moreover, high-frequency data has proven to be a valuable tool for examining price formation, discovery, and speculative bubbles.

This research stream indicates that the literature on cryptocurrencies is vast, with a range of studies exploring their higher volatility than conventional currencies (e.g., Katsiampa 2017; Dwyer 2015) and internally-driven nature (e.g., Baek and Elbeck 2015), making it highly speculative (Yermack 2015). However, some argue that Bitcoin is a currency or synthetic commodity money with monetary value, not a speculative investment (Blau 2017, 2018; Selgin 2015), although it possesses both speculative and financial asset properties (Kristoufek 2015) and competes with other cryptocurrencies (Gandal and Halaburda 2016). By studying Bitcoin's price formation mechanism, Ciaian et al. (2016b) report that speculators influence Bitcoin prices but that macroeconomic factors only affect them in the short term. Subsequently, Ciaian et al. (2018) argue that Bitcoin's transactions and speculative demand significantly impact its price formation. Meanwhile, Hu et al. (2019) suggest that prices usually form through negotiations and strategic trading.

However, price deviation across exchanges varies (Brandvold et al. 2015), with price discovery driven by shocks (Makarov and Schoar 2020). Using data from several exchanges, Brandvold et al. (2015) were the first to examine Bitcoin's price discovery mechanism by applying the econometric approaches of Hasbrouck (1995) and Gonzalo and Granger (1995). They argue that the exchanges with the highest trading volumes are pronounced price leaders concerning information sharing and find the United States BTC-e and Japan's Mtgox to be price setters or leaders. Pagnottoni and Dimpfl (2019) find that price discovery largely takes place on China-based OKcoin, Baur and Dimpfl (2019), Corbet et al. (2018b) find that spot prices lead the process, and Fassas et al. (2020) and Kapar and Olmo (2019) find that Bitcoin futures are dominant. Giudici and Polinesi (2021) and Giudici and Pagnottoni (2020) find Bitstamp, Coinbase, and Bitfinex to lead and Kraken as a follower exchange. Chang and Shi (2020) found Bitcoin to be a highly dominant cryptocurrency driving price discovery at the market level.

In addition to examining the short-term effects of speculators and macroeconomic factors, researchers have examined the endogeneity of price dynamics and the potential for bubbles. For example, the endogeneity of price dynamics is an important concept for understanding the dynamics of price bubbles because it explains how investors' expectations can drive prices. The endogeneity of price dynamics is the idea that investors' expectations of future prices are based on current prices. This can lead to a feedback loop of rising prices resulting from increased expectations of future prices. Price behavior in price discovery and bubbles in the Bitcoin market are two sides of the debate. Thus, explosiveness distorts the price discovery process. Turanova (2017) holds that Bitcoin's price discovery mechanism is unlikely to operate without an extreme price rise, suggesting its true value is higher than its current level. By contrast, Ché and Fry (2015) argue that the intrinsic value of a cryptocurrency is zero and that its exponential growth is a bubble. As discussed earlier, Bouoiyour and Selmi

(2015), Bouoiyour et al. (2016), Corbet et al. (2018a) and Kristoufek (2013) consider Bitcoin a speculative bubble rather than a currency.

Fry and Cheah (2016) find a negative bubble in Bitcoin and Ripple, with Ripple's spillover intensifying price drops in Bitcoin. Fry (2018) identifies bubbles in Bitcoin and Ethereum and argues that boom-bust cycles could occur without bubbles. Cheung et al. (2015) identified multiple transitory and three major bubbles in Bitcoin, with bursts corresponding to major events in the market. Bariviera et al. (2018) applied permutation information theory quantifiers to study the high-frequency price dynamics of 12 cryptocurrencies during a bubble and bust in the starting month of 2018. They found that cryptocurrencies demonstrate distinct dynamics, indicating they are not homogenous assets. Corbet et al. (2018a) reported Bitcoin to be in the bubble phase after crossing a \$1000 value. Bouri et al. (2019a) examine the link between explosive periods in the cryptocurrency market and find multidirectional co-explosivity, not necessarily from older to newer or larger to smaller markets.

There is a space for future research to study the relative price discovery of stablecoins, gold-backed cryptocurrencies, and tokens. These assets can contribute to price discovery and the crypto market efficiency. Moreover, the degree of price deviation and integration between these digital currencies during the onset of specific events, such as COVID-19 and the Ukraine-Russia war, may help broaden the understanding of overall cryptocurrency market behavior. As proposed by Su et al. (2022), it is important to examine the dramatic variations in the price discovery of Bitcoin at the intraday level in the post-COVID period. The explosivity or bubbles in cryptocurrency markets (Cheung et al. 2015), co-explosivity (Bouri et al. 2019a), price explosiveness, and the role of tweets (Shahzad et al. 2022) have been examined. However, the bubble contagion or spillover between cryptocurrencies and other financial assets can also be examined. The impact of supply and demand on the boom and bust of bubbles can be analyzed, along with using supply and demand graphs to simulate boom and bust periods. The connection and coherency of pre- and post-price explosiveness in the crypto market would be another avenue for future research, as information dynamics tools involving the microstructure in the cryptocurrency market may provide early warning signals of crashes. As Vasiliaskaite et al. (2022) suggest, the price and liquidity information dynamics concerning the microstructure in times of price explosiveness can be examined in the future.

Diversification, hedge, and safe-haven assets

In times of crisis, economic and financial shocks distort return predictability and price discovery processes. Smaller cryptocurrencies may start following larger ones (Vidal-Tomás et al. 2019), herding behavior tends to increase with uncertainty (Bouri et al. 2019c), and increasing prices can create a potential market bubble that can burst anytime. Additionally, in the cryptocurrency market, cryptocurrencies portray different patterns of volatility spillover owing to the difference in the structure of return and volatility clusters among them (Sensoy et al. 2021). The highly market cap cryptocurrencies, such as Bitcoin, Ethereum, and Litecoin, act as both transmitters and receivers of volatility in the crypto market (Polat and Kabakçı Günay 2021), while low cap ones, such as Mailsafe Coin may also act as its transmitters (Yi et al. 2018). This shock transmission results in lower diversification benefits. In such differing situations, investors start adjusting their

investments and opt for portfolio optimization or hedging strategies. In particular, during periods of downturn, rising demand for hedging and safe haven assets may drive up their prices, leading to inefficiency in the market. Moreover, for the cryptocurrency market, several factors, such as the price formation process and limited liquidity, may lead to unreliable safe haven assets (Smales 2019).

This research stream discusses the cryptocurrency literature, which includes cryptocurrencies in financial asset portfolios as diversifiers, hedges, and safe havens. In addition to the daily interdependencies within cryptocurrency markets (e.g., Ciaian and Rajcaniova 2018), studies have examined diversification opportunities using high-frequency data (e.g., Katsiampa et al. 2022; Sifat et al. 2019; Yarovaya and Zięba 2022). Bitcoin investment possesses the most distinctive features: remarkably high average returns and volatility and a lower correlation with other financial assets. Its inclusion, even in a small fraction, dramatically improves the portfolio's risk-return trade-off (Brière et al. 2015) and diversifies the portfolios (Guesmi et al. 2019; Platanakis and Urquhart 2020). As a financial asset, it is a useful instrument for portfolio, risk management, and market sentiment analysis based on its value-storing and exchanging benefits (Dyhrberg 2016a). Cryptocurrencies offer diversification benefits over other financial assets in short-term investment horizons (Corbet et al. 2018c). Similarly, Guesmi et al. (2019) report that including Bitcoin, gold, emerging equity markets, and oil in a portfolio can significantly decrease portfolio risk. Bitcoin offers income hedging as well.

Bitcoin displays hedging abilities like gold against market risk (Dyhrberg 2016b). It can act as a diversifier and poor hedge for the US dollar, stock, bond, gold, oil, and commodity markets. In contrast, its safe haven properties are especially visible in extreme downward movements in Asian stock markets. Data frequency matters to Bitcoin investors as its properties vary across time horizons (Bouri et al. 2017a). It acts as a strong hedge and safe haven against fluctuations in commodity market indices (Bouri et al. 2017b). However, Klein et al. (2018) find no hedging ability against a decline in equity prices, and it can hedge against uncertainties (Bouri et al. 2017c). In intraday trading, Urquhart and Zhang (2019) find that it can diversify the risk of the Japanese yen and Australian and Canadian dollars; hedge against the euro, Swiss franc, and pound; and act as a safe haven for the Swiss franc, Canadian dollar, and pound. Shahzad et al. (2019) find a weak safe haven ability of Bitcoin, commodities, and gold against global stock markets, with varying properties across equity market indices. Shahzad et al. (2020) find distinctive safe haven and hedge properties of Bitcoin and gold in G7 stock markets. Bouri et al. (2020a) find evidence that Bitcoin, Ripple, and Stellar are safe havens for US equity indices, whereas Monero and Litecoin do so for the US equity market index. Bitcoin has the least dependence on other assets and a superior safe-haven ability compared to gold and commodities (Bouri et al. 2020b).

Recently, investor concerns over the COVID-19 outbreak have led to research on the role of Bitcoin as a safe haven asset. Corbet et al. (2020a) find that investors are more inclined to view digital currency as a safe haven. However, a few studies (e.g., Conlon and McGee 2020; Corbet et al. 2020b) suggest cryptocurrencies may even increase contagion. Unlike Tether, Conlon et al. (2020) indicate that Bitcoin and Ethereum do not act as safe havens for most equity markets. Yousaf and Ali (2020) reveal that the portfolios of Bitcoin, Litecoin, and Ethereum are costlier and more effective in hedging during the

pandemic. Finally, Das et al. (2020) conclude that Bitcoin is better at hedging crude oil uncertainty than commodities and gold but not the US dollar.

It is possible to examine liquidity spillovers in cryptocurrencies to identify diversification benefits. This behavior can also be examined across assets. Diversification opportunities can be identified by examining the linkages among cryptocurrencies, meme stocks, and rare-earth stocks, considering various investment horizons. Since COVID-19 and its induced financial market turbulence have been the initial tests of the safe haven ability of Bitcoin (Kristoufek 2020), it is important to assess the safe haven property of Bitcoin by considering the differential impacts of the intensity and type of crisis. Another possible line of future research could be the assessment of the hedging effectiveness and safe haven ability of Bitcoin and other cryptocurrencies in the recovery phase of the COVID-19 pandemic and during the Russia-Ukraine War. The impact of health- and war-induced crises may provide new insights, depending on the nature of the events. Gkillas et al. (2020) suggest the inclusion of Bitcoin, gold, and oil in a single portfolio to analyze diversification benefits while studying the spillover effects of skewness, kurtosis, and jumps. Baur and Hoang (2021) find that the six largest stablecoins act as safe havens against Bitcoin, and Baumöhl and Vyrost (2020) find a few stable coins that act as safe havens against other top cryptocurrencies. There are many prospective avenues for examining the safe haven ability of stable coins and tokens (compared with unstable cryptocurrencies) against other assets. The symmetric or asymmetric multifractality and detrended correlation analysis of safe haven assets, including cryptocurrencies, stablecoins, and other financial assets, is a potential topic to explore. Since cryptocurrencies are becoming less influential, except Bitcoin, dApps, and Protocols, which are receiving much attention from investors (Katsiampa et al. 2022), upcoming research can focus on these distinctive cryptocurrencies in their market analysis.

Avenues of future research

Research opportunities opened by cryptocurrencies and Bitcoin in the scientific domain have prompted an in-depth examination of their future paths and influences. Various digital currencies, such as stablecoins, altcoins, and gold-backed cryptocurrencies, combined with the gradual progress of legalization in some countries, have led researchers to explore the financial properties of these currencies.

In this section, we offer a few future research questions that do not unconditionally fit into one of the four previously mentioned research streams: What are the causes of the cryptocurrency market crash in 2022? How do investors perceive the cryptocurrency market's future? Is there a need to revisit pre-crash research findings empirically? How do Bitcoin's hard and soft forks affect intraday reversal and momentum? What are the causal patterns of Bitcoin and other cryptocurrencies? What is the impact of changing regulations on the cryptocurrency market? What is the impact of an increase in decentralized finance (DeFi) on the cryptocurrency market? What is the impact of institutional investors on the cryptocurrency market? What effects do cryptocurrency derivatives have on the cryptocurrency market? What is the impact of news events on the cryptocurrency market? What are the effects of cryptocurrency mining on the cryptocurrency markets? What are the environmental impacts of cryptocurrency mining? What pricing models are used in cryptocurrency exchanges? What is the role of social

media in influencing the cryptocurrency market? What are the effects of algorithmic trading on the cryptocurrency markets? What are the effects of “whales” on cryptocurrency markets? What challenges do stakeholders in the crypto market face, and how can they overcome them?

Conclusions

In recent years, the intensified use of high-frequency data has revolutionized the analysis of cryptocurrencies, which are now actively traded 24/7 across global markets. We adopted a comprehensive bibliometric technique, leveraging co-citation and keyword co-occurrence analyses of 189 pertinent papers extracted from multidisciplinary domains in the Scopus database from 2015 to 2022. Our findings illuminate the expanding literature within the cryptocurrency market and shed light on leading articles, eminent authors, prominent institutions, reputable journals, and influential countries actively contributing to this domain.

Through a meticulous analysis of a bibliometric network and a thorough content assessment of scholarly articles, we identify and delineate four primary research streams that shape the discourse within the cryptocurrency market. These include studies focused on (1) examining the intricate dynamics of return and volatility behavior, encompassing predictive models and the phenomenon of abrupt fluctuations within cryptocurrencies; (2) analyzing the inherent inefficiencies within the cryptocurrency landscape; (3) investigating the mechanisms of price discovery, including its formation, potential manipulation, and the emergence of speculative bubbles within cryptocurrency markets; and (4) evaluating the diversification benefits, hedging strategies, and safe haven properties, particularly on the flagship cryptocurrency Bitcoin.

In our analysis, we meticulously pinpointed the critical gaps and unexplored avenues within each research stream, thereby providing scholars with comprehensive insights into potential future directions for research utilizing high-frequency data in the cryptocurrency domain. It is worth noting that, as Zha et al. (2020) highlighted, the study of investor behavior in the context of cryptocurrencies necessitates a multidimensional and integrated interdisciplinary approach. Therefore, the trajectory of cryptocurrency research transcends the confines of any single discipline, necessitating collaboration across diverse academic fields and methodologies.

It is imperative to acknowledge that while this study offers significant insights into research conducted using high-frequency data on the cryptocurrency market, it is constrained by its reliance on the Scopus database and its focus on the 24/7 trading nature of cryptocurrencies. Moving forward, the scope of this study can be expanded to encompass a broader spectrum of financial assets and alternate databases, such as the Web of Science and SpringerLink, to capture a holistic view of the evolving landscape within the realm of digital financial assets. As bibliometric studies continue to serve as influential tools for highlighting the growing impact of scholarly works and journals within specific domains, our research lays a strong foundation for further exploration and advancement in the realm of cryptocurrency research and analysis.

The insights gained from our comprehensive analysis of high-frequency data in the cryptocurrency market have significant practical and policy implications for stakeholders. As the cryptocurrency landscape continues to expand and evolve, investors,

financial regulators, and market participants can leverage identified research streams and trends to make informed decisions, manage risks, and develop robust strategies that capitalize on the unique properties of digital assets. Policymakers can use their findings to establish a more comprehensive regulatory framework that addresses the intricacies of the cryptocurrency market, thereby fostering transparency, stability, and investor protection. By embracing emerging research trends and addressing the highlighted gaps, stakeholders can foster a more resilient and secure cryptocurrency ecosystem aligned with the evolving demands of global financial markets. In addition, our study underscores the significance of interdisciplinary collaboration and the integration of diverse analytical tools in the study of cryptocurrency dynamics, underscoring the need for a cohesive and interdisciplinary approach that incorporates insights from fields such as economics, finance, computer science, and data analytics to ensure a holistic understanding of the multifaceted nature of the cryptocurrency market.

Abbreviations

TPA	Total publications of an author are a measure of the academic output of a researcher.
TPS	Total number of publications of a source or journal
AC	Affiliated countries or a country from which the publishing author is affiliated
TPC	Total number of publications of authors affiliated with a country that is used as a metric to gauge the research and academic output of that country
TCA	Total citations of an author are a measure of the impact of a researcher.
TCS	Total number of citations of a source or journal
TCC	Total number of citations of authors affiliated with a country that is used as a metric to gauge the research impact of that country.
TCJ	Total citations of journals
C/A	Citations per journal

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Author contributions

MA carried out conceptualization, methodology, software, formal analysis and writing. SJHS carried out conceptualization, supervision and writing—review and editing. LY carried out supervision, review and editing. All authors read and approved the final manuscript.

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Declarations

Competing interests

We have no competing interests to disclose.

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References

- Aalborg HA, Molnár P, de Vries JE (2019) What can explain the price, volatility and trading volume of Bitcoin? *Finance Res Lett* 29:255–265
- Akyildirim E, Goncu A, Sensoy A (2021) Prediction of cryptocurrency returns using machine learning. *Ann Oper Res* 297(1):3–36
- Alexander C, Dakos M (2020) A critical investigation of cryptocurrency data and analysis. *Quant Finance* 20(2):173–188
- Alexander C, Heck DF, Kaeck A (2022) The role of binance in bitcoin volatility transmission. *Appl Math Finance* 29(1):1–32
- Alonso-Monsalve S, Suárez-Cetrulo AL, Cervantes A, Quintana D (2020) Convolution on neural networks for high-frequency trend prediction of cryptocurrency exchange rates using technical indicators. *Expert Syst Appl* 149:113250
- Alvarez-Ramirez J, Rodríguez E, Ibarra-Valdez C (2018) Long-range correlations and asymmetry in the Bitcoin market. *Physica A* 492:948–955

- Ampah JD, Yusuf AA, Afrane S, Jin C, Liu H (2021) Reviewing two decades of cleaner alternative marine fuels: towards IMO's decarbonization of the maritime transport sector. *J Clean Prod* 320:128871
- Andersen TG, Bollerslev T, Diebold FX (2007) Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *Rev Econ Stat* 89(4):701–720
- Andersen TG, Bollerslev T, Diebold FX, Labys P (2003) Modeling and forecasting realized volatility. *Econometrica* 71(2):579–625
- Anderson TG, Bollerslev T, Diebold FX, Labys P (1999) The distribution of exchange rate volatility, vol. 6961. National Bureau of Economic Research
- Aria M, Cuccurullo C (2017) bibliometrix: an R-tool for comprehensive science mapping analysis. *J Informet* 11(4):959–975
- Arouxet MB, Bariviera AF, Pastor VE, Vampa V (2022) Covid-19 impact on cryptocurrencies: evidence from a wavelet-based Hurst exponent. *Physica A* 596:127170
- Aslan A, Sensoy A (2020) Intraday efficiency-frequency nexus in the cryptocurrency markets. *Financ Res Lett* 35:101298
- Baek C, Elbeck M (2015) Bitcoins as an investment or speculative vehicle? A first look. *Appl Econ Lett* 22(1):30–34
- Bakar NA, Rosbi S, Uzaki K (2017) Cryptocurrency framework diagnostics from Islamic finance perspective: a new insight of Bitcoin system transaction. *Int J Manag Sci Bus Adm* 4(1):19–28
- De Bakker FG, Groenewegen P, Den Hond F (2005) A bibliometric analysis of 30 years of research and theory on corporate social responsibility and corporate social performance. *Bus Soc* 44(3):283–317
- Balcilar M, Bourri E, Gupta R, Roubaud D (2017) Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Econ Model* 64:74–81
- Ballis A, Verousis T (2022) Behavioural finance and cryptocurrencies. *Review of Behavioral Finance*, (ahead-of-print)
- Bariviera AF (2017) The inefficiency of Bitcoin revisited: a dynamic approach. *Econ Lett* 161:1–4
- Bariviera AF, Basgall MJ, Hasperué W, Naiouf M (2017) Some stylized facts of the Bitcoin market. *Physica A* 484:82–90
- Bariviera AF, Merediz-Solà I (2021) Where do we stand in cryptocurrencies economic research? A survey based on hybrid analysis. *J Econ Surv* 35(2):377–407
- Bariviera AF, Zunino L, Rosso OA (2018) An analysis of high-frequency cryptocurrencies prices dynamics using permutation-information-theory quantifiers. *Chaos Interdisc J Nonlinear Sci* 28(7)
- Barndorff-Nielsen OE, Shephard N (2002) Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *J R Stat Soc Ser B (statistical Methodology)* 64(2):253–280
- Barndorff-Nielsen OE, Shephard N (2003) Realized power variation and stochastic volatility models. *Bernoulli* 9(2):243–265
- Barndorff-Nielsen OE, Shephard N (2004) Power and bipower variation with stochastic volatility and jumps. *J Financ Economet* 2(1):1–37
- Barndorff-Nielsen OE, Shephard N (2006) Econometrics of testing for jumps in financial economics using bipower variation. *J Financ Economet* 4(1):1–30
- Baumöhl E, Vyrost T (2020) Stablecoins as a crypto safe haven? Not all of them!. <http://hdl.handle.net/10419/215484>
- Baur DG, Dimpfl T (2019) Price discovery in bitcoin spot or futures? *J Futur Mark* 39(7):803–817
- Baur DG, Hoang LT (2021) A crypto safe haven against Bitcoin. *Financ Res Lett* 38:101431
- Bergsli LØ, Lind AF, Molnár P, Polasik M (2022) Forecasting volatility of Bitcoin. *Res Int Bus Financ* 59:101540
- Blasco N, Corredor P, Satrústegui N (2022) The witching week of herding on bitcoin exchanges. *Financial Innov* 8(1):1–18
- Blau BM (2017) Price dynamics and speculative trading in bitcoin. *Res Int Bus Financ* 41:493–499
- Blau BM (2018) Price dynamics and speculative trading in Bitcoin. *Res Int Bus Financ* 43:15–21
- Bleher J, Dimpfl T (2019) Today I got a million, tomorrow, I don't know: on the predictability of cryptocurrencies by means of Google search volume. *Int Rev Financ Anal* 63:147–159
- Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. *J Econom* 31(3):307–327
- Bollerslev T, Litvinova J, Tauchen G (2006) Leverage and volatility feedback effects in high-frequency data. *J Financ Economet* 4(3):353–384
- Borri N (2019) Conditional tail-risk in cryptocurrency markets. *J Empir Financ* 50:1–19
- Bouoiyour J, Selmi R, Tiwari AK, Olayeni OR (2016) What drives Bitcoin price. *Econ Bull* 36(2):843–850
- Bouoiyour J, Selmi R (2015) What does Bitcoin look like?. *Ann Econ Finance* 16(2)
- Bouri E, Gupta R, Roubaud D (2019c) Herding behaviour in cryptocurrencies. *Financ Res Lett* 29:216–221
- Bouri E, Gupta R, Tiwari AK, Roubaud D (2017c) Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Financ Res Lett* 23:87–95
- Bouri E, Jalkh N, Molnár P, Roubaud D (2017b) Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Appl Econ* 49(50):5063–5073
- Bouri E, Lau CKM, Lucey B, Roubaud D (2019b) Trading volume and the predictability of return and volatility in the cryptocurrency market. *Financ Res Lett* 29:340–346
- Bouri E, Molnár P, Azzi G, Roubaud D, Hagfors LI (2017a) On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Financ Res Lett* 20:192–198
- Bouri E, Shahzad SJH, Roubaud D (2019a) Co-explosivity in the cryptocurrency market. *Financ Res Lett* 29:178–183
- Bouri E, Shahzad SJH, Roubaud D (2020a) Cryptocurrencies as hedges and safe-havens for US equity sectors. *Q Rev Econ Finance* 75:294–307
- Bouri E, Shahzad SJH, Roubaud D, Kristoufek L, Lucey B (2020b) Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *Q Rev Econ Finance* 77:156–164
- Brandvold M, Molnár P, Vagstad K, Valstad OCA (2015) Price discovery on Bitcoin exchanges. *J Int Finan Markets Inst Money* 36:18–35
- Brauneis A, Mestel R (2018) Price discovery of cryptocurrencies: Bitcoin and beyond. *Econ Lett* 165:58–61
- Brauneis A, Mestel R, Riordan R, Theissen E (2022) Bitcoin unchained: determinants of cryptocurrency exchange liquidity. *J Empir Financ* 69:106–122
- Brauneis A, Mestel R, Theissen E (2021) What drives the liquidity of cryptocurrencies? A long-term analysis. *Finance Res Lett* 39:101537

- Brière M, Oosterlinck K, Szafarz A (2015) Virtual currency, tangible return: portfolio diversification with bitcoin. *J Asset Manag* 16(6):365–373
- Bunjaku F, Gjorgieva-Trajkowska O, Miteva-Kacarski E (2017) Cryptocurrencies—advantages and disadvantages. *J Econ* 2(1):31–39
- Böhme R, Christin N, Edelman B, Moore T (2015) Bitcoin: Economics, technology, and governance. *J Econ Perspect* 29(2):213–238
- Caporale GM, Gil-Alana L, Plastun A (2018) Persistence in the cryptocurrency market. *Res Int Bus Financ* 46:141–148
- Caporale GM, Kang WY, Spagnolo F, Spagnolo N (2021) Cyber-attacks, spillovers and contagion in the cryptocurrency markets. *J Int Finan Markets Inst Money* 74:101298
- Carbone A, Castelli G, Stanley HE (2004) Time-dependent Hurst exponent in financial time series. *Physica A* 344(1–2):267–271
- Carrick J (2016) Bitcoin as a complement to emerging market currencies. *Emerg Mark Financ Trade* 52(10):2321–2334
- Chan S, Chu J, Zhang Y, Nadarajah S (2022) An extreme value analysis of the tail relationships between returns and volumes for high frequency cryptocurrencies. *Res Int Bus Financ* 59:101541
- Chang L, Shi Y (2020) Does Bitcoin dominate the price discovery of the Cryptocurrencies market? A time-varying information share analysis. *Oper Res Lett* 48(5):641–645
- Chaum D (1983) Blind signatures for untraceable payments. In: *Advances in Cryptology: Proceedings of Crypto 82*, Springer US, Boston, MA. pp 199–203
- Cheah ET, Fry J (2015) Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Econ Lett* 130:32–36
- Cheah ET, Mishra T, Parhi M, Zhang Z (2018) Long memory interdependency and inefficiency in Bitcoin markets. *Econ Lett* 167:18–25
- Chen X, Ghysels E (2011) News—good or bad—and its impact on volatility predictions over multiple horizons. *Rev Financial Stud* 24(1):46–81
- Chen C, Liu L, Zhao N (2020) Fear sentiment, uncertainty, and bitcoin price dynamics: the case of COVID-19. *Emerg Mark Finance Trade* 56(10):2298–2309
- Cheung A, Roca E, Su JJ (2015) Crypto-currency bubbles: an application of the Phillips–Shi–Yu (2013) methodology on Mt Gox Bitcoin prices. *Appl Econ* 47(23):2348–2358
- Choi KH, Kang SH, Yoon SM (2022) Herding behaviour in Korea’s cryptocurrency market. *Appl Econ* 54(24):2795–2809
- Christensen K, Oomen RC, Podolskij M (2014) Fact or friction: jumps at ultra high frequency. *J Financ Econ* 114(3):576–599
- Chu J, Chan S, Nadarajah S, Osterrieder J (2017) GARCH modelling of cryptocurrencies. *J Risk Financ Manag* 10(4):17
- Chu J, Chan S, Zhang Y (2020) High frequency momentum trading with cryptocurrencies. *Res Int Bus Financ* 52:101176
- Chu J, Chan S, Zhang Y (2021) Bitcoin versus high-performance technology stocks in diversifying against global stock market indices. *Physica A* 580:126161
- Chu J, Nadarajah S, Chan S (2015) Statistical analysis of the exchange rate of bitcoin. *PLoS ONE* 10(7):e0133678
- Chu J, Zhang Y, Chan S (2019) The adaptive market hypothesis in the high frequency cryptocurrency market. *Int Rev Financ Anal* 64:221–231
- Ciaian P, Rajcaniova M (2018) Virtual relationships: short-and long-run evidence from BitCoin and altcoin markets. *J Int Finan Markets Inst Money* 52:173–195
- Ciaian P, Rajcaniova M, Kancs DA (2016a) The economics of BitCoin price formation. *Appl Econ* 48(19):1799–1815
- Ciaian P, Rajcaniova M, Kancs DA (2016b) The digital agenda of virtual currencies: Can BitCoin become a global currency? *IseB* 14(4):883–919
- Ciaian P, Kancs DA, Rajcaniova M (2018) The price of Bitcoin: GARCH evidence from high frequency data. arXiv preprint <https://arxiv.org/abs/1812.09452>
- Cobo MJ, López-Herrera AG, Herrera-Viedma E, Herrera F (2011) Science mapping software tools: review, analysis, and cooperative study among tools. *J Am Soc Inform Sci Technol* 62(7):1382–1402
- Comerio N, Strozzi F (2019) Tourism and its economic impact: a literature review using bibliometric tools. *Tour Econ* 25(1):109–131
- Conlon T, Corbet S, McGee RJ (2020) Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. *Res Int Bus Financ* 54:101248
- Conlon T, McGee R (2020) Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Financ Res Lett* 35:101607
- Cont R (2001) Empirical properties of asset returns: stylized facts and statistical issues. *Quant Finance* 1(2):223
- Corbet S, Hou YG, Hu Y, Larkin C, Oxley L (2020a) Any port in a storm: cryptocurrency safe-havens during the COVID-19 pandemic. *Econ Lett* 194:109377
- Corbet S, Katsiampa P (2020) Asymmetric mean reversion of Bitcoin price returns. *Int Rev Financ Anal* 71:101267
- Corbet S, Larkin C, Lucey B (2020b) The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Financ Res Lett* 35:101554
- Corbet S, Lucey B, Peat M, Vigne S (2018b) Bitcoin Futures—What use are they? *Econ Lett* 172:23–27
- Corbet S, Lucey B, Urquhart A, Yarovaya L (2019) Cryptocurrencies as a financial asset: a systematic analysis. *Int Rev Financ Anal* 62:182–199
- Corbet S, Lucey B, Yarovaya L (2018a) Datestamping the Bitcoin and Ethereum bubbles. *Financ Res Lett* 26:81–88
- Corbet S, Meegan A, Larkin C, Lucey B, Yarovaya L (2018c) Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Econ Lett* 165:28–34
- Corsi F (2009) A simple approximate long-memory model of realized volatility. *J Financ Economet* 7(2):174–196
- Das D, Le Roux CL, Jana RK, Dutta A (2020) Does Bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US Dollar. *Financ Res Lett* 36:101335
- Demir E, Gozgor G, Lau CKM, Vigne SA (2018) Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Financ Res Lett* 26:145–149
- Diebold FX, Yilmaz K (2012) Better to give than to receive: predictive directional measurement of volatility spillovers. *Int J Forecast* 28(1):57–66

- Diebold FX, Yilmaz K (2014) On the network topology of variance decompositions: measuring the connectedness of financial firms. *J Econom* 182(1):119–134
- Dimitrova V, Fernández-Martínez M, Sánchez-Granero MA, Trinidad Segovia JE (2019) Some comments on Bitcoin market (in) efficiency. *PLoS ONE* 14(7):e0219243
- Ding Y, Chowdhury GG, Foo S (2001) Bibliometric cartography of information retrieval research by using co-word analysis. *Inf Process Manage* 37(6):817–842
- Ding Y, Cronin B (2011) Popular and/or prestigious? Measures of scholarly esteem. *Inf Process Manage* 47(1):80–96
- Dong B, Jiang L, Liu J, Zhu Y (2022) Liquidity in the cryptocurrency market and commonalities across anomalies. *Int Rev Financ Anal* 81:102097
- Drożdż S, Gebarowski R, Minati L, Oświęcimka P, Watorek M (2018) Bitcoin market route to maturity? Evidence from return fluctuations, temporal correlations and multiscaling effects. *Chaos Interdiscip J Nonlinear Sci* 28(7):071101
- Drożdż S, Kwapien J, Oświęcimka P, Rak R (2010) Quantitative features of multifractal subtleties in time series. *EPL (europhysics Letters)* 88(6):60003
- Drożdż S, Kwapien J, Oświęcimka P, Stanisław T, Watorek M (2020) Complexity in economic and social systems: cryptocurrency market at around COVID-19. *Entropy* 22(9):1043
- Dwyer GP (2015) The economics of Bitcoin and similar private digital currencies. *J Financ Stab* 17:81–91
- Dyhrberg AH (2016a) Bitcoin, gold and the dollar—a GARCH volatility analysis. *Financ Res Lett* 16:85–92
- Dyhrberg AH (2016b) Hedging capabilities of bitcoin. Is it the virtual gold? *Financ Res Lett* 16:139–144
- Dyhrberg AH, Foley S, Svec J (2018) How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets. *Econ Lett* 171:140–143
- Van Eck NJ, Waltman L (2014) Visualizing bibliometric networks. In: Ding Y, Rousseau R, Wolfram D (eds) *Measuring Scholarly Impact*. Springer, Berlin, pp 285–320
- Engle RF (1982) Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econom J Econom Soc* 50(4):987–1007
- Eross A, McGroarty F, Urquhart A, Wolfe S (2019) The intraday dynamics of bitcoin. *Res Int Bus Financ* 49:71–81
- Fahimnia B, Sarkis J, Davarzani H (2015) Green supply chain management: a review and bibliometric analysis. *Int J Prod Econ* 162:101–114
- Fama EF (1970) Efficient capital markets: a review of theory and empirical work. *J Financ* 25(2):383–417
- Fang L, Bouri E, Gupta R, Roubaud D (2019) Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? *Int Rev Financ Anal* 61:29–36
- Fang F, Ventre C, Basios M, Kanthan L, Martínez-Rego D, Wu F, Li L (2022) Cryptocurrency trading: a comprehensive survey. *Financial Innov* 8(1):1–59
- Fassas AP, Papadamou S, Koulis A (2020) Price discovery in bitcoin futures. *Res Int Bus Financ* 52:101116
- Fry J (2018) Booms, busts and heavy-tails: The story of Bitcoin and cryptocurrency markets? *Econ Lett* 171:225–229
- Fry J, Cheah ET (2016) Negative bubbles and shocks in cryptocurrency markets. *Int Rev Financ Anal* 47:343–352
- Fung K, Jeong J, Pereira J (2022) More to cryptos than bitcoin: a GARCH modelling of heterogeneous cryptocurrencies. *Financ Res Lett* 47:102544
- Gandal N, Halaburda H (2016) Can we predict the winner in a market with network effects? Competition in cryptocurrency market. *Games* 7(3):16
- Gandal N, Hamrick JT, Moore T, Oberman T (2018) Price manipulation in the Bitcoin ecosystem. *J Monet Econ* 95:86–96
- García-Corral FJ, Cordero-García JA, de Pablo-Valenciano J, Uribe-Toril J (2022) A bibliometric review of cryptocurrencies: how have they grown? *Financial Innov* 8(1):1–31
- Giudici P, Pagnottoni P (2020) Vector error correction models to measure connectedness of Bitcoin exchange markets. *Appl Stoch Model Bus Ind* 36(1):95–109
- Giudici P, Polinesi G (2021) Crypto price discovery through correlation networks. *Ann Oper Res* 299(1):443–457
- Gkillas K, Bouri E, Gupta R, Roubaud D (2020) Spillovers in higher-order moments of crude oil, gold, and Bitcoin. *Q Rev Econ Finance* 84:398–406
- Gkillas K, Gupta R, Wohar ME (2018) Volatility jumps: the role of geopolitical risks. *Financ Res Lett* 27:247–258
- Gkillas K, Katsiampa P, Konstantatos C, Tsagkanos A (2022) Discontinuous movements and asymmetries in cryptocurrency markets. *Eur J Finance*. <https://doi.org/10.1080/1351847X.2021.2015416>
- Glantz M, Kissell RL (2013) *Multi-asset risk modeling: techniques for a global economy in an electronic and algorithmic trading era*. Academic Press, London
- Gonzalo J, Granger C (1995) Estimation of common long-memory components in cointegrated systems. *J Bus Econ Stat* 13(1):27–35
- Gradojevic N, Kukolj D, Adcock R, Djakovic V (2022) Forecasting Bitcoin with technical analysis: A not-so-random forest? *Int J Forecast* 39(1):1–17
- Gradojevic N, Tsiakas I (2021) Volatility cascades in cryptocurrency trading. *J Empir Financ* 62:252–265
- Greaves A, Au B (2015) Using the bitcoin transaction graph to predict the price of bitcoin. *No Data* 8:416–443
- Grobys K, Huynh TLD (2022) When Tether says “JUMP!” Bitcoin asks “How low?” *Financ Res Lett* 47:102644
- Guesmi K, Saadi S, Abid I, Ftiti Z (2019) Portfolio diversification with virtual currency: evidence from bitcoin. *Int Rev Financ Anal* 63:431–437
- Hansen PR, Huang Z (2016) Exponential GARCH modeling with realized measures of volatility. *J Bus Econ Stat* 34(2):269–287
- Hansen PR, Huang Z, Shek HH (2012) Realized GARCH: a joint model for returns and realized measures of volatility. *J Appl Economet* 27(6):877–906
- Hasbrouck J (1995) One security, many markets: determining the contributions to price discovery. *J Financ* 50(4):1175–1199
- Holub M, Johnson J (2018) Bitcoin research across disciplines. *Inf Soc* 34(2):114–126
- Hu B, McInish T, Miller J, Zeng L (2019) Intraday price behavior of cryptocurrencies. *Financ Res Lett* 28:337–342
- Huang X, Tauchen G (2005) The relative contribution of jumps to total price variance. *J Financ Economet* 3(4):456–499
- Härdle WK, Harvey CR, Reule RC (2020) Understanding cryptocurrencies. *J Financ Economet* 18(2):181–208

- Jalal RNUD, Alon I, Paltrinieri A (2021) A bibliometric review of cryptocurrencies as a financial asset. *Technol Anal Strateg Manag*. <https://doi.org/10.1080/09537325.2021.1939001>
- Jalal RUD, Sargiacomo M, Sahar NU, Fayyaz UER (2020) Herding behavior and cryptocurrency: market asymmetries, inter-dependency and intra-dependency. *J Asian Finance Econ Bus* 7(7):27–34
- Ji Q, Bourri E, Kristoufek L, Lucey B (2021) Realised volatility connectedness among Bitcoin exchange markets. *Financ Res Lett* 38:101391
- Ji Q, Bourri E, Lau CKM, Roubaud D (2019) Dynamic connectedness and integration in cryptocurrency markets. *Int Rev Financ Anal* 63:257–272
- Jiang S, Li X, Wang S (2021) Exploring evolution trends in cryptocurrency study: from underlying technology to economic applications. *Financ Res Lett* 38:101532
- Jiang Y, Nie H, Ruan W (2018) Time-varying long-term memory in Bitcoin market. *Financ Res Lett* 25:280–284
- Jiang ZQ, Xie WJ, Zhou WX, Sornette D (2019) Multifractal analysis of financial markets: a review. *Rep Prog Phys* 82(12):125901
- Johnson B, Laszka A, Grossklags J, Vasek M, Moore T (2014) Game-theoretic analysis of DDoS attacks against Bitcoin mining pools. In: *International Conference on Financial Cryptography and Data Security*, Springer, Berlin, Heidelberg. pp 72–86
- Kantelhardt JW, Zschiegner SA, Koscielny-Bunde E, Havlin S, Bunde A, Stanley HE (2002) Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A* 316(1–4):87–114
- Kapar B, Olmo J (2019) An analysis of price discovery between Bitcoin futures and spot markets. *Econ Lett* 174:62–64
- Karalevicius V, Degrande N, De Weerd J (2018) Using sentiment analysis to predict interday Bitcoin price movements. *J Risk Finance* 19(1):56–75
- Katsiampa P (2017) Volatility estimation for Bitcoin: a comparison of GARCH models. *Econ Lett* 158:3–6
- Katsiampa P, Corbet S, Lucey B (2019) High frequency volatility co-movements in cryptocurrency markets. *J Int Financ Markets Inst Money* 62:35–52
- Katsiampa P, Yarovaya L, Zięba D (2022) High-Frequency connectedness between bitcoin and other top-traded crypto assets during the COVID-19 crisis. *J Int Financ Mark Inst Money* 79:101578
- Kayal P, Rohilla P (2021) Bitcoin in the economics and finance literature: a survey. *SN Bus Econ* 1(7):1–21
- Khuntia S, Pattanayak JK (2018) Adaptive market hypothesis and evolving predictability of bitcoin. *Econ Lett* 167:26–28
- Khuntia S, Pattanayak JK (2020) Adaptive long memory in volatility of intra-day bitcoin returns and the impact of trading volume. *Finance Res Lett* 32:101077
- Klein T, Thu HP, Walther T (2018) Bitcoin is not the New Gold—A comparison of volatility, correlation, and portfolio performance. *Int Rev Financ Anal* 59:105–116
- Koutmos D (2018) Bitcoin returns and transaction activity. *Econ Lett* 167:81–85
- Kristoufek L (2013) BitCoin meets Google Trends and Wikipedia: quantifying the relationship between phenomena of the Internet era. *Sci Rep* 3(1):1–7
- Kristoufek L (2015) What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PLoS ONE* 10(4):e0123923
- Kristoufek L (2018) On Bitcoin markets (in) efficiency and its evolution. *Physica A* 503:257–262
- Kristoufek L (2020) Grandpa, grandpa, tell me the one about Bitcoin being a safe haven: new evidence from the COVID-19 pandemic. *Front Phys* 8:296
- Lahmiri S, Bekiros S (2019) Cryptocurrency forecasting with deep learning chaotic neural networks. *Chaos Solitons Fractals* 118:35–40
- Levine-Clark M, Gil EL (2008) A comparative citation analysis of Web of science, scopus, and google scholar. *J Bus Financ Librariansh* 14(1):32–46
- Li X, Li S, Xu C (2020) Price clustering in Bitcoin market—an extension. *Financ Res Lett* 32:101072
- Li X, Qiao H, Wang S (2017) Exploring evolution and emerging trends in business model study: a co-citation analysis. *Scientometrics* 111(2):869–887
- Li X, Wang CA (2017) The technology and economic determinants of cryptocurrency exchange rates: the case of Bitcoin. *Decis Support Syst* 95:49–60
- Long S, Lucey B, Xie Y, Yarovaya L (2022) “I Just Like the Stock”: the role of reddit sentiment in the gamestop share rally. *Financ Rev* 58(1):19–37
- Makarov I, Schoar A (2020) Trading and arbitrage in cryptocurrency markets. *J Financ Econ* 135(2):293–319
- Mandaci PE, Cagli EC (2022) Herding intensity and volatility in cryptocurrency markets during the COVID-19. *Financ Res Lett* 46:102382
- McNally S, Roche J, Caton S (2018) Predicting the price of bitcoin using machine learning. In: *2018 26th euromicro international conference on parallel, distributed and network-based processing (PDP)*, pp 339–343. IEEE
- Mensi W, Al-Yahyaee KH, Al-Jarrah IMW, Vo XV, Kang SH (2020) Dynamic volatility transmission and portfolio management across major cryptocurrencies: evidence from hourly data. *N Am J Econ Finance* 54:101285
- Mensi W, Lee YJ, Al-Yahyaee KH, Sensoy A, Yoon SM (2019) Intraday downward/upward multifractality and long memory in Bitcoin and Ethereum markets: an asymmetric multifractal detrended fluctuation analysis. *Financ Res Lett* 31:19–25
- Merediz-Solà I, Bariviera AF (2019) A bibliometric analysis of bitcoin scientific production. *Res Int Bus Financ* 50:294–305
- Moral-Muñoz JA, Herrera-Viedma E, Santisteban-Espejo A, Cobo MJ (2020) Software tools for conducting bibliometric analysis in science: an up-to-date review. *Prof Inf*. <https://doi.org/10.3145/epi.2020.ene.03>
- Nadarajah S, Chu J (2017) On the inefficiency of Bitcoin. *Econ Lett* 150:6–9
- Naeem MA, Bourri E, Peng Z, Shahzad SJH, Vo XV (2021) Asymmetric efficiency of cryptocurrencies during COVID19. *Physica A* 565:125562
- Nakamoto S (2008) Bitcoin: a peer-to-peer electronic cash system. *Decentralized Business Review*, 21260
- Nakano M, Takahashi A, Takahashi S (2018) Bitcoin technical trading with artificial neural network. *Physica A* 510:587–609
- Nasir MA, Huynh TLD, Nguyen SP, Duong D (2019) Forecasting cryptocurrency returns and volume using search engines. *Financ Innov* 5(1):1–13

- Nguyen LH, Chevapatrakul T, Yao K (2020) Investigating tail-risk dependence in the cryptocurrency markets: a LASSO quantile regression approach. *J Empir Financ* 58:333–355
- Oświęcimka P, Drożdż S, Forczek M, Jadach S, Kwapień J (2014) Detrended cross-correlation analysis consistently extended to multifractality. *Phys Rev E* 89(2):023305
- Oświęcimka P, Kwapień J, Drożdż S (2006) Wavelet versus detrended fluctuation analysis of multifractal structures. *Phys Rev E* 74(1):016103
- Pagnottoni P, Dimpfl T (2019) Price discovery on Bitcoin markets. *Digital Finance* 1(1):139–161
- Patel R, Goodell JW, Oriani ME, Paltrinieri A, Yarovaya, (2022) A bibliometric review of financial market integration literature. *Int Rev Financ Anal* 80:102035
- Patton AJ, Sheppard K (2015) Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Rev Econ Stat* 97(3):683–697
- Paul J, Bhukya R (2021) Forty-five years of International Journal of Consumer Studies: a bibliometric review and directions for future research. *Int J Consum Stud* 45(5):937–963
- Peng Y, Albuquerque PHM, de Sá JMC, Padula AJA, Montenegro MR (2018) The best of two worlds: forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. *Expert Syst Appl* 97:177–192
- Persson O (1994) The intellectual base and research fronts of JASIS 1986–1990. *J Am Soc Inf Sci* 45(1):31–38
- Philippas D, Philippas N, Tziogkidis P, Rijba H (2020) Signal-herding in cryptocurrencies. *J Int Finan Markets Inst Money* 65:101191
- Phillip A, Chan JS, Peiris S (2018) A new look at cryptocurrencies. *Econ Lett* 163:6–9
- Phillip A, Chan J, Peiris S (2019) On long memory effects in the volatility measure of cryptocurrencies. *Financ Res Lett* 28:95–100
- Platanakis E, Urquhart A (2020) Should investors include bitcoin in their portfolios? A portfolio theory approach. *Br Account Rev* 52(4):100837
- Polat O, Kabakçı Günay E (2021) Cryptocurrency connectedness nexus the COVID-19 pandemic: evidence from time-frequency domains. *Stud Econ Financ* 38(5):946–963
- Potter WJ, Levine-Donnerstein D (1999) Rethinking validity and reliability in content analysis. *J Appl Commun Res* 27(3):258–284
- Qiu Y, Wang Y, Xie T (2021) Forecasting Bitcoin realized volatility by measuring the spillover effect among cryptocurrencies. *Econ Lett* 208:110092
- Quiroga-García R, Pariente-Martínez N, Arenas-Parra M (2022) Evidence for round number effects in cryptocurrencies prices. *Financ Res Lett* 47:102811
- Ramona O, Cristina MS, Raluca S (2019) Bitcoin in the scientific literature—a bibliometric study. *Stud Bus Econ* 14(3):160–174
- Rognone L, Hyde S, Zhang SS (2020) News sentiment in the cryptocurrency market: an empirical comparison with Forex. *Int Rev Financ Anal* 69:101462
- Ruane F, Tol RS (2007) *Economics in Ireland* (No. 180). ESRI Working Paper
- Ruggeri G, Orsi L, Corsi S (2019) A bibliometric analysis of the scientific literature on Fairtrade labelling. *Int J Consum Stud* 43(2):134–152
- Scaillet O, Treccani A, Trevisan C (2020) High-frequency jump analysis of the bitcoin market. *J Financ Economet* 18(2):209–232
- Selgin G (2015) Synthetic commodity money. *J Financ Stab* 17:92–99
- Sensoy A (2019) The inefficiency of Bitcoin revisited: a high-frequency analysis with alternative currencies. *Financ Res Lett* 28:68–73
- Sensoy A, Silva TC, Corbet S, Tabak BM (2021) High-frequency return and volatility spillovers among cryptocurrencies. *Appl Econ* 53(37):4310–4328
- Shahzad SJH, Anas M, Bouri E (2022) Price explosiveness in cryptocurrencies and Elon Musk's tweets. *Finance Res Lett* 47:102695
- Shahzad SJH, Bouri E, Roubaud D, Kristoufek L (2020) Safe haven, hedge and diversification for G7 stock markets: gold versus bitcoin. *Econ Model* 87:212–224
- Shahzad SJH, Bouri E, Roubaud D, Kristoufek L, Lucey B (2019) Is Bitcoin a better safe-haven investment than gold and commodities? *Int Rev Financ Anal* 63:322–330
- Shen D, Urquhart A, Wang P (2019) Does twitter predict Bitcoin? *Econ Lett* 174:118–122
- Shen CW, Chang LC, Su TC (2020) Research development of Bitcoin: a network and concept linking analysis. *Library Hi Tech*.
- Shi S, Shi Y (2021) Bitcoin futures: trade it or ban it? *Eur J Finance* 27(4–5):381–396
- Sifat IM, Mohamad A, Shariff MSBM (2019) Lead-lag relationship between bitcoin and ethereum: evidence from hourly and daily data. *Res Int Bus Financ* 50:306–321
- da Silva Filho AC, Maganini ND, de Almeida EF (2018) Multifractal analysis of Bitcoin market. *Physica A* 512:954–967
- Smales LA (2019) Bitcoin as a safe haven: Is it even worth considering? *Financ Res Lett* 30:385–393
- Small H (1973) Co-citation in the scientific literature: a new measure of the relationship between two documents. *J Am Soc Inf Sci* 24(4):265–269
- Sousa A, Calçada E, Rodrigues P, Borges AP (2022) Cryptocurrency adoption: a systematic literature review and bibliometric analysis. *EuroMed J Bus* 17(3):374–390
- Stavroyiannis S, Babalos V, Bekiros S, Lahmiri S, Uddin GS (2019) The high frequency multifractal properties of Bitcoin. *Physica A* 520:62–71
- Su F, Wang X, Yuan Y (2022) The intraday dynamics and intraday price discovery of bitcoin. *Res Int Bus Financ* 60:101625
- Takaishi T (2018) Statistical properties and multifractality of Bitcoin. *Physica A* 506:507–519
- Takaishi T (2020) Rough volatility of Bitcoin. *Financ Res Lett* 32:101379
- Takaishi T (2021) Time-varying properties of asymmetric volatility and multifractality in Bitcoin. *PLoS ONE* 16(2):e0246209

- Takaishi T, Adachi T (2020) Market efficiency, liquidity, and multifractality of Bitcoin: a dynamic study. *Asia-Pacific Finan Markets* 27(1):145–154
- Tauchen G, Zhou H (2011) Realized jumps on financial markets and predicting credit spreads. *J Econom* 160(1):102–118
- Thies S, Molnár P (2018) Bayesian change point analysis of Bitcoin returns. *Financ Res Lett* 27:223–227
- Tiwari AK, Jana RK, Das D, Roubaud D (2018) Informational efficiency of Bitcoin—An extension. *Econ Lett* 163:106–109
- Tschorsch F, Scheuermann B (2016) Bitcoin and beyond: a technical survey on decentralized digital currencies. *IEEE Commun Surv Tutor* 18(3):2084–2123
- Turanoglu G (2017) Is bitcoin a bubble? 29 December. <http://www.nasdaq.com/article/is-bitcoin-a-bubble-cm898150>. Accessed 1 July 2022
- Urquhart A (2016) The inefficiency of Bitcoin. *Econ Lett* 148:80–82
- Urquhart A (2017) Price clustering in Bitcoin. *Econ Lett* 159:145–148
- Urquhart A (2018) What causes the attention of Bitcoin? *Econ Lett* 166:40–44
- Urquhart A, Zhang H (2019) Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. *Int Rev Financ Anal* 63:49–57
- Van Eck NJ, Waltman L (2019) Accuracy of citation data in Web of Science and Scopus. arXiv preprint <https://arxiv.org/abs/1906.07011>
- Vasiliauskaitė V, Lillo F, Antulov-Fantulin N (2022) Information dynamics of price and liquidity around the 2017 Bitcoin markets crash. *Chaos Interdiscip J Nonlinear Sci* 32(4):043123
- Vidal-Tomás D (2021) An investigation of cryptocurrency data: the market that never sleeps. *Quantit Finance* 21(12):2007–2024
- Vidal-Tomás D (2022) All the frequencies matter in the Bitcoin market: an efficiency analysis. *Appl Econ Lett* 29(3):212–218
- Vidal-Tomás D, Ibañez A (2018) Semi-strong efficiency of Bitcoin. *Financ Res Lett* 27:259–265
- Vidal-Tomás D, Ibañez AM, Farinós JE (2019) Herding in the cryptocurrency market: CSSD and CSAD approaches. *Financ Res Lett* 30:181–186
- Waltman L, Van Eck NJ (2013) A smart local moving algorithm for large-scale modularity-based community detection. *Eur Phys J B* 86:1–14
- Waltman L, Van Eck NJ, Noyons EC (2010) A unified approach to mapping and clustering of bibliometric networks. *J Informet* 4(4):629–635
- Wang M, Li X, Wang S (2021) Discovering research trends and opportunities of green finance and energy policy: a data-driven scientometric analysis. *Energy Policy* 154:112295
- Wang J, Ngene GM (2020) Does Bitcoin still own the dominant power? An intraday analysis. *Int Rev Financ Anal* 71:101551
- Wang J, Wang X (2021) COVID-19 and financial market efficiency: evidence from an entropy-based analysis. *Financ Res Lett* 42:101888
- Wei WC (2018) Liquidity and market efficiency in cryptocurrencies. *Econ Lett* 168:21–24
- Wen Z, Bouri E, Xu Y, Zhao Y (2022) Intraday return predictability in the cryptocurrency markets: momentum, reversal, or both. *N Am J Econ Finance* 62:101733
- Whittaker J (1989) Creativity and conformity in science: titles, keywords and co-word analysis. *Soc Stud Sci* 19(3):473–496
- Yarovaya L, Matkovskyy R, Jalan A (2021) The effects of a “black swan” event (COVID-19) on herding behavior in cryptocurrency markets. *J Int Finan Markets Inst Money* 75:101321
- Yarovaya L, Zięba D (2022) Intraday volume-return nexus in cryptocurrency markets: a novel evidence from cryptocurrency classification. *Res Int Bus Finance* 60:101592
- Yermack D (2015) Is Bitcoin a real currency? An economic appraisal. *Handbook of digital currency*. Academic Press, London, pp 31–43
- Yi S, Xu Z, Wang GJ (2018) Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *Int Rev Financ Anal* 60:98–114
- Yousaf I, Ali S (2020) Discovering interlinkages between major cryptocurrencies using high-frequency data: new evidence from COVID-19 pandemic. *Financ Innov* 6(1):1–18
- Yu M (2019) Forecasting Bitcoin volatility: the role of leverage effect and uncertainty. *Physica A* 533:120707
- Yue Y, Li X, Zhang D, Wang S (2021) How cryptocurrency affects economy? A network analysis using bibliometric methods. *Int Rev Financ Anal* 77:101869
- Zargar FN, Kumar D (2019) Informational inefficiency of Bitcoin: a study based on high-frequency data. *Res Int Bus Finance* 47:344–353
- Zha Q, Kou G, Zhang H, Liang H, Chen X, Li CC, Dong Y (2020) Opinion dynamics in finance and business: a literature review and research opportunities. *Financ Innov* 6:1–22
- Zhang Y, Chan S, Chu J, Nadarajah S (2019a) Stylised facts for high frequency cryptocurrency data. *Physica A* 513:598–612
- Zhang Y, Chan S, Nadarajah S (2019b) Extreme value analysis of high-frequency cryptocurrencies. *High Freq* 2(1):61–69
- Zhang W, Wang P, Li X, Shen D (2018) The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average. *Physica A* 510:658–670
- Zheng Z, Xie S, Dai HN, Chen X, Wang H (2018) Blockchain challenges and opportunities: a survey. *Int J Web Grid Serv* 14(4):352–375
- Zupic I, Cater T (2015) Bibliometric methods in management and organization. *Organ Res Methods* 18(3):429–472
- Zyskind G, Nathan O (2015) Decentralizing privacy: using blockchain to protect personal data. In: 2015 IEEE Security and Privacy Workshops, pp 180–184. IEEE

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